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THESIS

PRELIMINARY DESIGN OF AN AUTONOMOUS UNDERWATER VEHICLE USING MULTI-OBJECTIVE OPTIMIZATION

by

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The objectives I used in the model are the minimization of the power needed to propel the vehicle and the maximization of both the weight of the energy section and the total range. Implementation of both the model and the optimization are carried out using Matlab, particularly the global optimization toolbox and the multi-objective genetic algorithm solver, whereas a special case of two objectives is implemented in Excel using Visual Basic and Excel solver.

This research also explores the potential for a designer to use goals in the multi-objective optimization as well as approaches that let a designer choose one particular solution once all Pareto optimal solutions are found.

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PRELIMINARY DESIGN OF AN AUTONOMOUS UNDERWATER VEHICLE USING MULTI-OBJECTIVE OPTIMIZATION

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LIST OF ACRONYMS AND ABBREVIATIONS

Acronyms

AUV	autonomous underwater vehicle
DMFC	direct and indirect methanol fuel cell
EHP	effective horsepower
EMO	evolutionary multi-objective optimization
GA	genetic algorithm
GFRP	glass-fiber reinforced plastic
MCFC	molten carbonate fuel cell
NSGA	non-dominated sorting genetic algorithm
PAFC	phosphoric acid fuel cell
PC	propulsive coefficient
PEMFC	proton exchange membrane fuel cell
PHP	propulsive horsepower
PO	Pareto optimal
PSO	particle swarm optimization
SE	systems engineer
SEP	systems engineering process
SHP	shaft horsepower
SOFC	solid oxide fuel cell
THP	thrust horsepower
UUV	underwater unmanned vehicle

Nomenclature

Symbol	Description
c_A	roughness correlation allowance coefficient
c_F	friction coefficient
c_r	pressure difference coefficient
D	diameter
E_{tot}	total available energy
L_a	length of aft part
L_f	length of forward part
L_{pmb}	length of the parallel body
L_{tot}	overall length
n_a	aft form factor
n_f	forward form factor
R_t	total drag force
t	thrust deduction coefficient
V	vehicle speed
η_p	propeller efficiency
η_O	open water efficiency
η_R	relative rotative efficiency
η_M	machinery efficiency
η_H	hull efficiency

Bold (i.e., $\boldsymbol{h}$, $\boldsymbol{\omega}$ or $\bar{x}$ or x^*) indicates vector, while unbolded (i.e., h, ω) indicates scalar. The International System of Units (SI) is used for all variables.

ACKNOWLEDGMENTS

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A special thanks to my wife, Eirini, and my daughter, Kallia, for their encouragement, moral support and sacrifices.

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DEDICATION

This thesis is dedicated to my mother.

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I. INTRODUCTION

A. MOTIVATION

Both military operations and the civilian sector have been using autonomous vehicles for over six decades. Recent military experiences, in particular, have showed their significant role in naval operations. Therefore, an increase in demand for autonomous vehicles in the near future is expected. Autonomous underwater vehicles (AUVs) have been used in the collection of ocean data, the survey of marine environments, the observation of animal life, as well as for military purposes. In any case, the optimization of various and often conflicting design objectives is always the goal for designers of such versatile vehicles. In a survey of missions for unmanned undersea vehicles [1], the authors present and analyze various types of AUVs and define the current status of technologies of computing and robotics, navigation, communications and networking, power sources and propulsion, and materials.

Designing a complex system is a demanding and intensive task. A ship's designer, as any designer of complex systems, faces a variety of stakeholder requirements, needs, variables and constraints. It is his job to take all these inputs into consideration and present an optimal design, reflecting the necessary trade-offs and feasible design region.

The latest published *Unmanned Systems Integrated Roadmap FY2013–2038* of the U.S. Secretary of Defense [2] states:

> Operational issues will be more complex as the pace of technological change accelerates. Designing systems to easily accept technological improvement capabilities and support multiple mission needs will be increasingly important.
>
> Many of today's persistent systems rely on efficient forms of propulsion that are sustainable for long-endurance missions. Other systems require propulsion that can be optimized for long range and endurance or optimized for high speed. Additionally, systems such as UUVs face challenges to extend endurance into months with energy technologies that are air independent. Certainly powering for long-term persistence is a large challenge.

Early decisions made in systems design are quite important and determine the output to a great extent. The systems engineering approach usually requires an iterative design process. Multi-objective optimization can help the designer to incorporate an overall systems engineering approach into the design process. Most real-world problems have several objectives that need to be optimized at the same time; that is, they are multi-objective in nature.

Moreover, recent technological developments and improvements have created the potential to improve overall power and propulsion performance and therefore overall vehicle capability. To integrate such technology into an AUV design requires a firm understanding of all the design parts.

B. OBJECTIVES

The main objective of this work is to use multi-objective optimization to help the designer of an AUV find the best solutions when there are conflicting objectives. First, I begin with an introduction of the systems engineering design process and the background work for the multi-objective optimization process. Furthermore, I investigate and analyze the existing multi-objective optimization methods in decision making. I focus on various design aspects of an AUV, such as the hull design, the weight distribution, the propulsion and especially the power supply technology.

Then, I demonstrate the setup of the AUV model. I create a design space of several variables, constraints and objectives, and I search this design space for the best designs, or Pareto front, that includes the non-dominated solutions. Specifically, I am presenting an AUV model with three objectives to be optimized: namely the effective horsepower needed for overcoming the resistance of the vehicle, the weight of the energy section and the range of the required mission.

Implementation of both the model and the optimization process are carried out using Matlab, particularly the global optimization toolbox and the multi-objective genetic algorithm solver, whereas a special case of two objectives is implemented in Excel using Visual Basic and Excel solver.

Finally, I present the results of this work and some ideas for possible future work. The primary outcome of this work is to help system designers and specifically AUV designers map a design space and find optimal solutions taking into consideration existing constraints, as well as the stakeholders' objectives and requirements using multi-objective optimization techniques.

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II. DESIGN PROCESS

Systems engineering is an interdisciplinary approach that originated from large aerospace projects to manage project complexity due to the large number of parts, people and complex interfaces involved. It is a methodology developed over decades and is still evolving.

The U.S. Department of Defense states that:

> Systems engineering offers a technical framework to enable sound decision making relative to trade studies, system performance, risk, cost, and schedule. The successful instantiation of proven, disciplined systems engineering processes results in a total system solution that is adaptive to changing technical, production, and operating environments and to the needs of the use and is balanced among the multiple requirements, design considerations, design constraints, and program budgets. [3]

Systems engineers analyze system needs and define top-level features. They decompose the system and move top-level requirements to individual design areas. Furthermore, they maintain the baseline configuration, document changes and review the system at all phases of development. Systems engineering management includes the development phasing, a systems engineering process (SEP) and the life cycle integration as we can see in Figure 1.

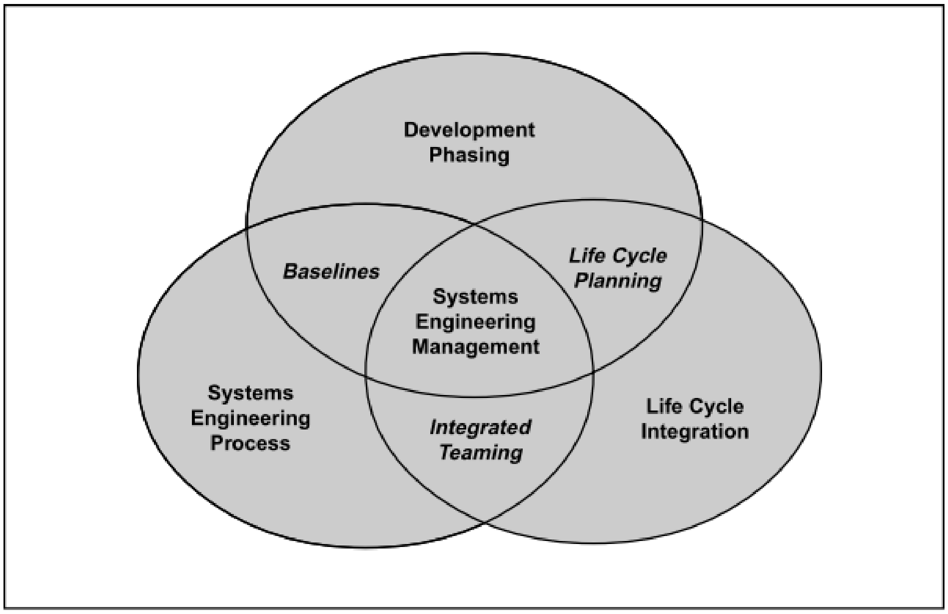

Figure 1. Activities of Systems Engineering Management. From [4].

The first part of SEP is the analysis of the system's functional behavior. The systems engineer (SE) partitions the whole system into functional areas and develops the appropriate functional requirements related to the mission. He should also take special care during that phase as problematic requirements may not be met. Developing and documenting a functional baseline as well as functional interfaces is a part of this phase of the SEP.

The second phase of the SEP includes analyzing top-level needs and then developing the specific requirement statements. The SE moves requirements to lower levels keeping them balanced across the entire system, and provides traceability and documentation for all requirements.

The next step is the verification of the functional and requirements analysis. First, the SE conducts an analysis of the subsystems and component behavior, taking into account vendors' or stakeholders' specifications, using analytic and/or computer models. Second, he conducts an analysis of the total system behavior through computer models and simulations.

The synthesis phase is the final part of SEP. Through synthesis the SE defines the configuration and the interfaces of the system and conducts the trade-off and risk analysis. Finally, he selects the preferred solutions (Figure 2).

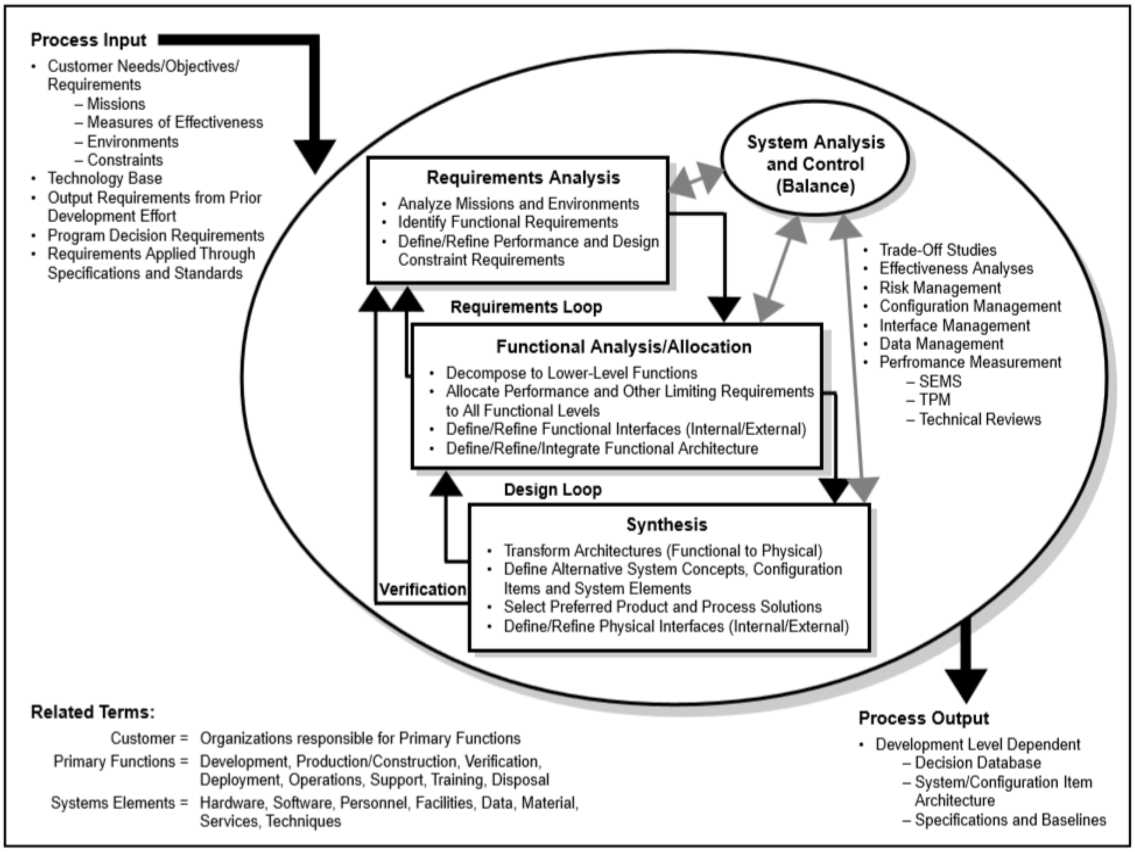

Figure 2. The Systems Engineering Process. From [4].

According to the *Naval Systems Engineering Guide* [5], the SE needs to apply these processes recursively and iteratively to define the system products of the system hierarchy from the top down, and then, to implement and transition the system products, from the bottom up to the user or customer. Figure 3 shows the sub-processes used in systems engineering, which are applicable to the engineering or reengineering of the end products that make up a system.

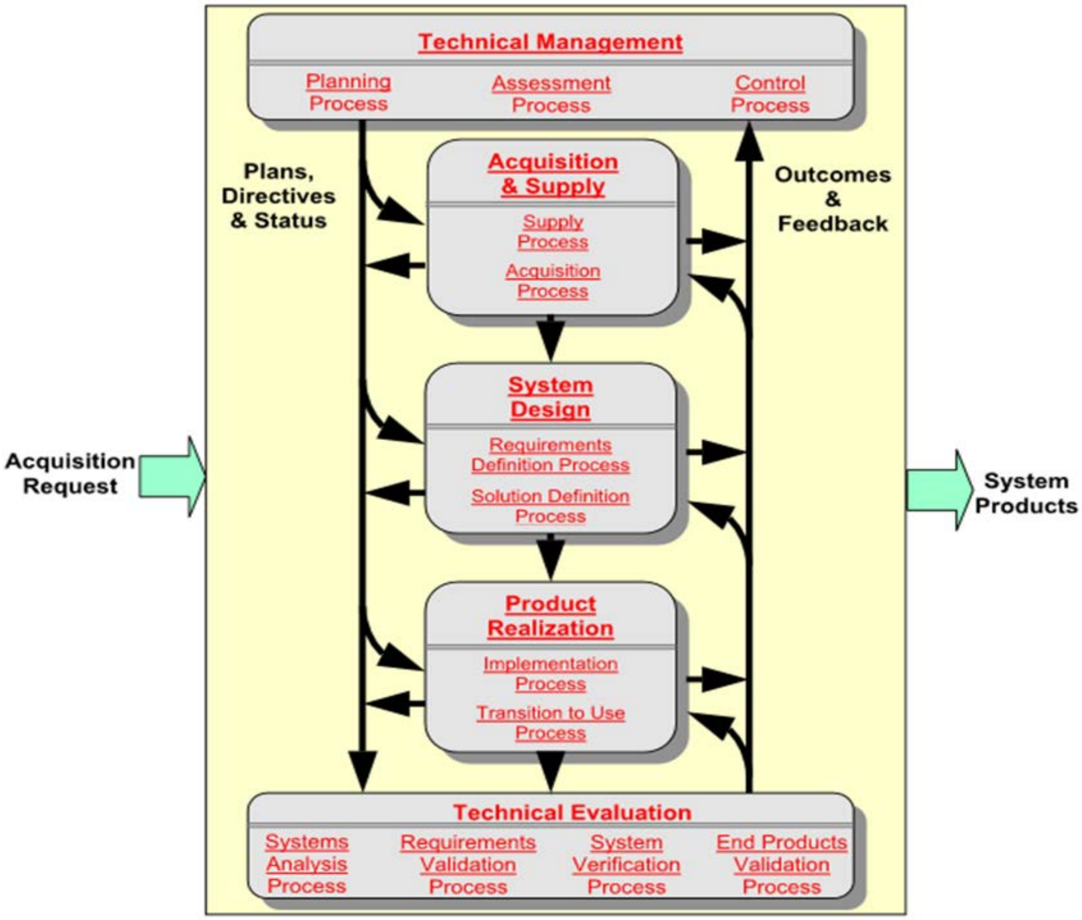

Figure 3. Relationship of Processes for Engineering a System. From [5].

There are two major system development models used in systems engineering, and both have strengths and weaknesses.

A. WATERFALL MODEL

Waterfall is the classic model that allows for easy planning and more precise estimation of the project's cost. This model is suited to projects whose requirements are well known and have an inflexible budget. Its structure minimizes wasted effort as it provides accuracy at each step of the project, so it works well for relatively technically inexperienced staff. A well-known weakness of the model is that the steps of the model do not interact with each other, making it less effective in overcoming problems that arise during development. Another drawback is that the budget should be available at the start

of project planning. This requirement is difficult for enterprises/organizations with limited budgets. Some implied management risks associated with the waterfall model are the dependence on well-known requirements prior to development, which is usually difficult in large projects, and the inability to adopt new technology that emerges during the development phase. Moreover, the customer cannot see the product until the completion of the project.

B. SPIRAL MODEL

The spiral model is a risk-reduction oriented model that breaks a project up into "mini" projects. It suits more complicated projects and lets them start, even though the requirements are not yet clear or known, and the problems or discrepancies can be corrected early as the nature of this model allows feedback in every stage. That means lower cost, among other benefits. On the other hand, this approach is more complicated and requires more experienced personnel to be successful. The decision maker cannot easily estimate the overall cost from the beginning, and there is the danger of the total cost exceeding the funding. Furthermore, inexperienced managers may have problems using the model, causing delays and increasing the cost of the whole project. Figure 4 shows the spiral model implemented into a submersible vehicle systems design. In this figure, we can see the iterative design process through the various loops for the conceptual, preliminary and contract design, beginning from the general arrangement and ending up with the cost estimate summary.

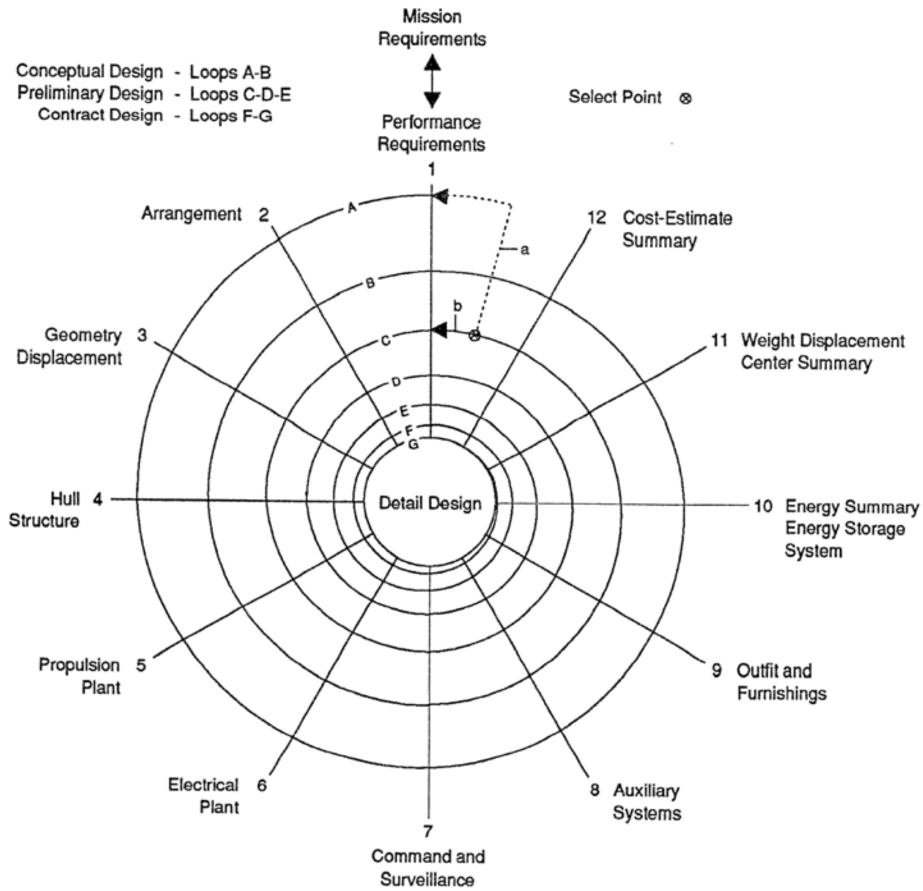

Figure 4. Submersible Vehicle Design Spiral. From [6].

One of the most important steps in designing a system is determining the objectives and the requirements. Stakeholders are the people who have an interest in the project and may have different and often contradicting objectives. Stakeholder analysis is the systematic gathering and analyzing of qualitative information to determine whose interests should be taken into account when developing and/or implementing a policy or program [7]. Stakeholder analysis is not just an examination of who the individual stakeholders are, but also of how their motives, interests, and values affect system development.

Early in the design phase, requirements extraction should follow a formal process to identify the stakeholders. The designer should not take the requirements as given but

he needs to validate those using interviews, to prioritize them and document them using a hierarchical structure for easy traceability.

The following discussion about the criteria of a good requirement follows the guidelines of [8]. Requirements are necessary for the system to meet real and prioritized needs. A good requirement should be verifiable; that is, one can ensure that the system under development meets the requirement. A good requirement should also be attainable; that is, it is feasible for the system to meet the requirement. Moreover, a good requirement is unambiguous and complete. In other words, the decision maker determines all known requirements, as well as all the conditions under which the requirement applies. Furthermore, the requirement should be consistent as it has to be met without conflicting with all other requirements. The decision maker needs also to define the requirements simply and clearly in order to be concise and traceable.

Figure 5 depicts the importance of requirements identification through showing the effect of requirements process investment on program costs for various NASA programs, such as the earth radiation budget satellite (ERB), the Hubble space telescope (HST) and the infrared astronomical observatory (IRAS). One can see that when the percentage of the requirements process investment is lower than 5% of the total cost, there is an 80%–200% project cost overrun. That overrun highlights the importance of requirements development that is dependent on the program strategy and the method used. It is widely accepted that the larger the project is the more difficult requirements extraction becomes, as there are many users, customers and stakeholders that have many conflicting needs and desires. Thus, it becomes more difficult to get the time and attention of key people.

In this chapter, I highlighted the challenges presented by the design process particularly in regard to the AUV design under the prism of systems engineering. I analyzed the major system development models, as well as the importance of objectives and requirements development. In the next chapter, I address some background information regarding the existing multi-objective optimization methods in decision making and how they can be applied when the objectives and the requirements are known.

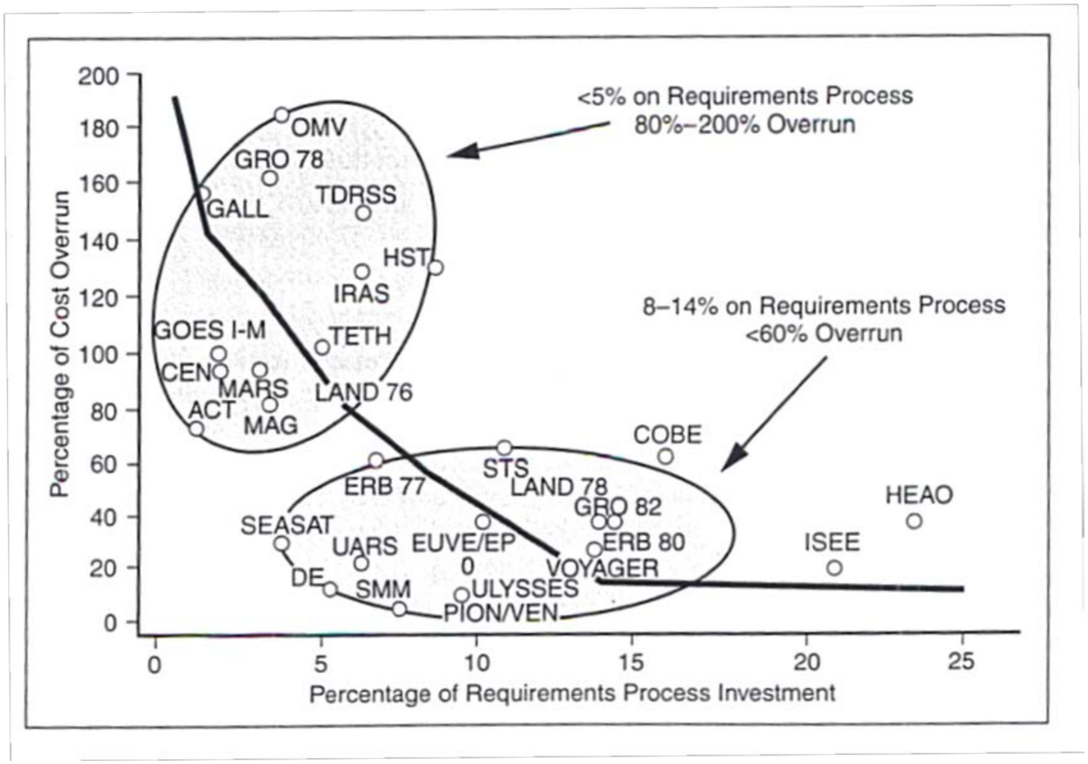

Figure 5. Effect of Requirements Process Investment on Program Costs. From [9].

III. MULTI-OBJECTIVE OPTIMIZATION

A. GENERAL DESCRIPTION AND DEFINITIONS

As discussed in the previous chapter, the importance of the requirements, as well as the objectives that come out of those requirements, becomes obvious. By employing a multi-objective optimization process, the designer can address some of the problems associated with the traditional design approaches, such as the waterfall or spiral model. The multi-objective optimization approach allows different steps to be designed concurrently. At the same time, optimization is at every step trying to exceed existing standards while reducing the resources needed. Optimization is the process of maximizing or minimizing a desired objective function while satisfying the prevailing constraints [10]. There are various methods dealing with different kinds of problems of unconstrained or constrained optimization, including linear programming, direct search methods for nonlinear optimization, integer and discrete programming and dynamic programming. Figure 6 shows a classification of optimization methods (derivative and non-derivative based). The derivative methods are fast, but they have some limitations, such as the necessity for the continuity of the objective function and a large probability of losing the global optimum and being stuck to a local optimum. Another drawback is that the choice of starting point influences the convergence. A thorough discussion on concepts of continuity, global and local optima and function convergence can be found in [10]. The non-derivative-based optimization techniques do not need derivative evaluations, and the optimization is performed by calculating the value of the objective function only. For more information on these methods the reader can find an extended bibliography at the end of this thesis.

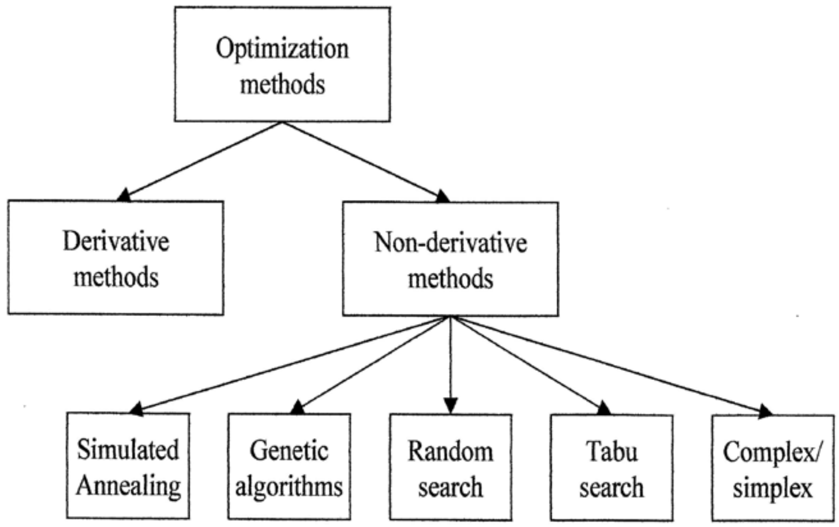

Figure 6. Classification of Optimization Methods in Derivative and Non-derivative Methods with Examples of Some Non-derivative Methods. From [11].

According to [10], to date, designers have been using optimization more as a design or decision aid, rather than for concept generation or detailed design. In this sense, optimization is an engineering tool. In real-life problems, there are several conflicting objectives that need to be considered simultaneously. Engineering design is clearly about making many decisions often under uncertainty and with multiple conflicting criteria. Figure 7 shows a classification of various methods for multi-objective optimization. In this study I use the multi-objective optimization, and more specifically the genetic algorithms, as a designing tool to find the optimal solutions having contradictory objectives.

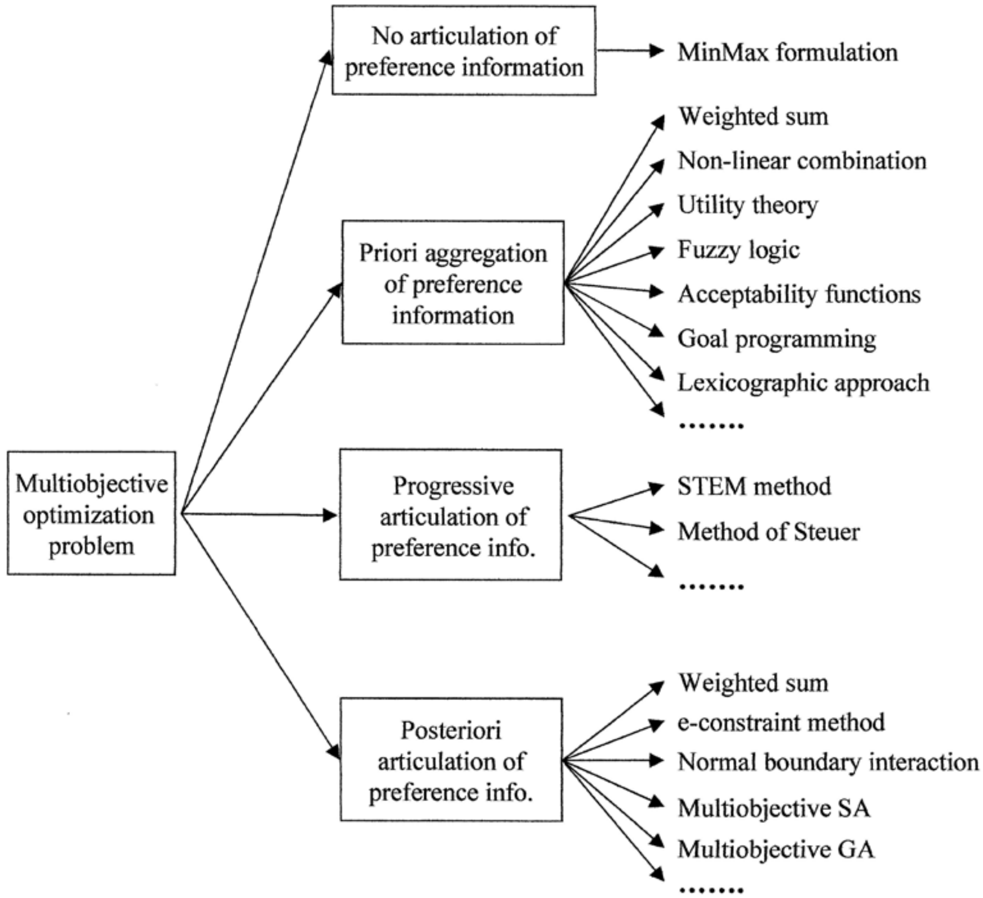

Figure 7. A Classification of Methods for Multi-objective Optimization. From [11].

Before discussing multi-objective optimization, I will give some general definitions of terms related to this method. A constraint is some relation that must be satisfied and an objective is some function that represents a requirement (something we need to minimize or maximize). A goal is some outcome that is desirable to achieve, but could be violated at some penalty to overall value of solution. In a mathematical sense the multi-objective optimization concept can be stated as:

minimize $f = \left[f_1\left(\overline{x}\right), f_2\left(\overline{x}\right), ..., f_n\left(\overline{x}\right) \right]$ subject to $\overline{x} \in$ S, with constraints

$$g_j\left(\overline{x}\right) \geq 0,\ j = 1, 2, ..., J$$
$$h_k\left(\overline{x}\right) = 0, k = 1, 2, ..., \mathrm{K}$$

S ⊂ R^n = feasible region formed by constraint functions

If the objective functions do not conflict with one another, all the objectives can be minimized simultaneously. One can solve a maximization problem by minimizing the negative of the objective function, and thus, the minimization form can be generalized. Normally, (marine) design problems include multiple conflicting objectives. When this is the case, the concept of Pareto optimality is generally used, as articulated by the Italian-French economist Vilfredo Pareto in 1906. It was originally proposed by Francis Y. Edgeworth and sometimes it is called Edgeworth-Pareto optimal, but I will use the most commonly accepted term: Pareto optimal (PO).

A point x* ϵ S is a global Pareto optimal, if there does not exist another point x ϵ S such that $f_j(x) \leq f_j(x^*)$ for all $\mathrm{j} = 1, ..., n$ and $f_j(x) < f_j(x^*)$ for at least one j.

> A point is Pareto optimal if it satisfies the constraints and is such that no criterion can be further improved without causing at least one of the other criteria to decline. A point is weakly Pareto optimal if it satisfies the constraints and one criterion remains constant while at least one of the other criteria declines. These definitions typically result in a set of optimal solutions rather than a single unique solution. [12]

Figure 8 provides a visualization of the nomenclature.

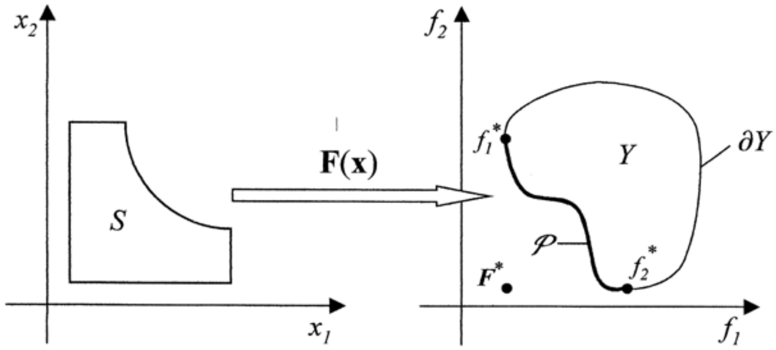

Figure 8. Parameter/Solution and Attribute Space Nomenclature for a Two Dimensional Problem with Two Objectives. From [11].

In large and complicated projects it is usually an analyst who is responsible for the mathematical side of the problem to meet the requirements and the given preferences. In the end, a decision maker needs to identify a final PO solution, that is, the best possible compromise. The decision maker knows the problem and can express preference relations.

B. BACKGROUND INFORMATION

The methods that need no preference information, like min-max and global criterion method [13], [14], [15], are not widely used in engineering design. Since no preferences from the designer are needed, the outcome is only one point on the Pareto front. The designer has to accept that point as the final solution. The min-max formulation is based on the minimization of the relative distance from a candidate solution to the utopian solution F* (Figure 8). The following formulation of a global criterion method is taken from [11].

$$\min d\left(\bar{x}\right) = \min\left[\sum_{j=1}^{k}\left(\frac{f_j\left(\bar{x}\right) - f_j^*}{f_j^*}\right)^p\right]^{\frac{1}{p}} \text{ subject to } \bar{x} \in \text{S}, 1 \leq \text{p} \leq \infty$$

The optimization problem becomes the minimization of the distance $d\left(\bar{x}\right)$. In this form, the nearest to the utopian solution results when $p=2$; that is, a weighted Euclidean distance of any point in the objective space from the ideal point is minimized, whereas, when a large p is used the form is called the weighted Tchebycheff problem that guarantees finding each and every PO solution [16]. The Archimedean goal-programming solution and the weighted sum solution correspond to the $p=1$ case. These are special forms of the more general formulation [12]. The decision maker can obtain various points on the Pareto front by giving different weightings to the single objectives according to his preferences.

The most easily and perhaps most widely used method is the weighted-sum approach. The multi-objective problem is converted to a single optimization problem and then the appropriate method is used.

$$\min \sum_{j=1}^{k} w_j f_j\left(\bar{x}\right) \text{ subject to } \bar{x} \in S,$$

where $w_j \geq 0$ for all j=1,…,n and $\sum_{j=1}^{k} w_j = 1$

This method is the most convenient one but has been frequently criticized, mainly because of correlation issues and nonlinear affects (non-convex problems). As a way to overcome the difficulties in solving problems having non-convex objective spaces, the $\in -$constraint method is used [16]. The values of the weights depend on the importance of each objective and a small change in weights changes the solution dramatically, whereas evenly distributed weights do not produce an evenly distributed representation of the Pareto optimal set. The various objectives can have different scales and units, so it is important the designer to normalize them using reference values obtained by solving the optimization problem for each objective (f_k^0). That way the objectives values are set in the range between zero and one. The generally used term for this approach is the normed weighted sum optimum that yields,

$$P[f(\bar{x})] = \sum_{j=1}^{k} [w_j f_j\left(\bar{x}\right) / f_k^0]$$

The value function method (or utility function method) uses a mathematical value function U that relates all objectives. The goal is to maximize the value function; that is, the preference of a solution must increase if one of the objective function values is decreased while keeping the other objective function values the same [16]. Miettinen [17] proved the following theorem:

> Let the value function U: $\mathbb{R}^M \to \mathbb{R}$ be strongly decreasing. Let U attain its maximum at f^*. Then, f^* is Pareto-optimal.

This method creates contours of the value function and the contour tangential to the PO front is the preferred solution (Figure 9). Using this method, the designer finds one solution at a time and by changing the parameters of the utility function he can find various PO solutions. The utility function is usually chosen to be a nonlinear function of the objectives. A more thorough discussion on the theory of value (or utility) functions can be found in [18].

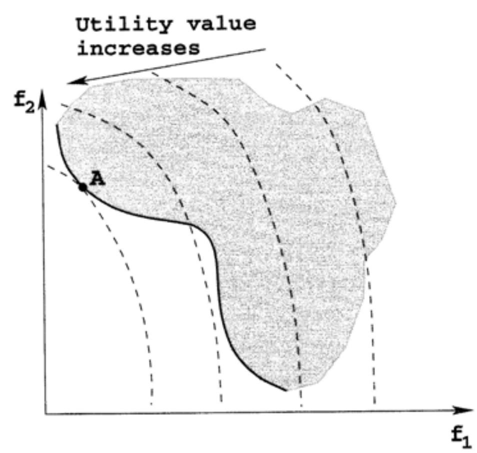

Figure 9. Contours of the Value Function. From [16].

The lexicographic ordering is an a priori method in which the decision maker has to specify an absolute order of importance for objectives. If the most important objective has a unique solution, the method stops and it gives a solution. Otherwise, the second most important objective is optimized such that the most important objective maintains its optimal value and so on. This method is quite robust. The less important objectives have very little chance to affect the final solution. If there is a clear distinction between the objectives' significance, it is easy for the designer to use this method. Even though a lot of people make decisions successively, it is usually difficult to determine the absolute order of importance in real life problems.

Goal programming is another a priori method that dates back to the mid-1950s. It was introduced in an application of a linear programming problem by Charnes et al. [19] and used in management models of linear programing. It asks the decision maker to specify goals, that is, aspiration levels for each objective function.

$$goal(f\left(\bar{x}\right)=\bar{t}),$$
$$\bar{x}\in S$$

The main idea is to find solutions that meet the goals and if this is not possible, then deviations from goals are minimized. In other words, the goal is to find a point in the design space that has the smallest deviation from the utopian solution. This method has been used in various marine applications [20], [21], [22]. It is implemented using the weighted approach, the lexicographic approach or a combination of the two, where a weighted sum of deviations is minimized in a priority-driven manner. There can be four different types of goal criteria [23].

$$Less\ than\ equal\ to: f\left(\bar{x}\right)\leq\bar{t}$$
$$Greater\ than\ equal\ to: f\left(\bar{x}\right)\geq\bar{t}$$
$$Equal\ to: f\left(\bar{x}\right)=\bar{t}$$
$$Within\ a\ range: f\left(\bar{x}\right)\in\left[\bar{t}_a,\bar{t}_b\right]$$

This method is widely used mainly because of its simplicity and because it gives the decision maker some freedom by setting goals and changing them accordingly. There is still the inherent drawback of having the user specify the importance of the objectives a priori.

There are some methods that need very little knowledge to be there a priori. They use progressive articulation of preference information from the decision maker as the direction of search, weight vector and reference points during the optimization process. There are various methods such as the ISWT method, Guess method, NIMBUS approach, STEM method, method of Steuer and Light beam search. More information about these methods can be found in [17].

All methods mentioned previously require some knowledge about the problem, and the PO solution will depend on the chosen weights or parameters. They convert a multi-objective optimization problem into a single-objective one and it depends on the efficiency of the single-objective optimization algorithm to find the PO solution. Thus, the preferences of the designer and his personal assumptions and expectations play a significant role in the final solution. These methods have been widely used in real-world multi-objective optimization applications mainly due to their simplicity and because they are easy to implement in a programming language.

Another category of multi-objective optimization methods includes the a posteriori articulation of preference information methods. They are used mainly in order to avoid the subjective judgment of the decision maker. Ideally, in a multi-objective optimization, the goal is to find the set of PO solutions by considering all objectives to be important. After a set of such solutions is found, the decision maker can choose a particular solution using higher-level information related to the problem, which is often non-technical, qualitative and experience driven. When the PO solutions are available, one can judge the pros and cons of each of these solutions based on this higher-level information and compare them to make a choice. Furthermore, the visual representation of the PO front makes it easier for the designer to choose especially if there are knee-points, which may well represent a natural preferred solution. A definition of a knee-point

suggested in a study [24] was based on finding two or more neighboring solutions and calculating the reflex angle, as shown in Figure 10:

> A knee point is the Pareto-optimal point having the maximum reflex angle computed from its neighbors. [24]

A knee-point is usually preferred over all the other PO solutions because the designer needs to pay a high cost in one objective to have a minor gain in another objective. It is noteworthy to mention that as the number of objectives increases visualization becomes harder. For two objectives, the PO front is at most a two-dimensional curve, and for three objectives, the PO front is at most a three-dimensional surface and so on.

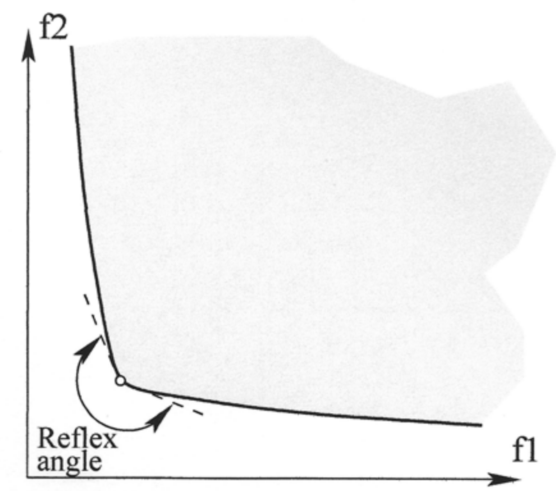

Figure 10. The Reflex Angle Based Definition of a Knee-Point. From [25].

C. EVOLUTIONARY OPTIMIZATION – GENETIC ALGORITHMS

Over the last two decades there has been an increasing interest in evolutionary multi-objective optimization (EMO) algorithms that follow the principles of the a posteriori articulation of preference information. A number of stochastic search strategies have been developed such as the tabu search, simulated annealing, ant colony optimization, genetic algorithms and particle swarm optimization.

The genetic algorithm (GA) is a search and optimization method, which uses random starting points and mimics the processing of chromosomes in the Darwinian principle of evolution [26]. The algorithm begins with a feasible random set that is first generated and used as a starting point, which is called a population with a fixed initial size or a number of individuals. Each individual is a chromosome, and is defined by optimization variables. The chromosome represents a possible solution to the optimization problem, and its length is affected by the number of optimization variables and their required precision. Also, each variable has to be bounded by a minimum and a maximum value [26]. The worst solutions are eliminated and best solutions kept throughout the iterative optimization process and used as starting points. After each generation (iteration), the individuals reproduce, survive, or disappear as a result of the action of a selection operator. Typically, the better an individual performs, the higher the probability it will be selected. The iteration phase ensures the genetic mix via mutation that introduces random modifications to an individual and cross-breeding, where one or several children are generated from a combination of two parents. Using these operations new regions in the search space are explored to find individuals that perform better. Thus, new individuals are constructed (Figure 11).

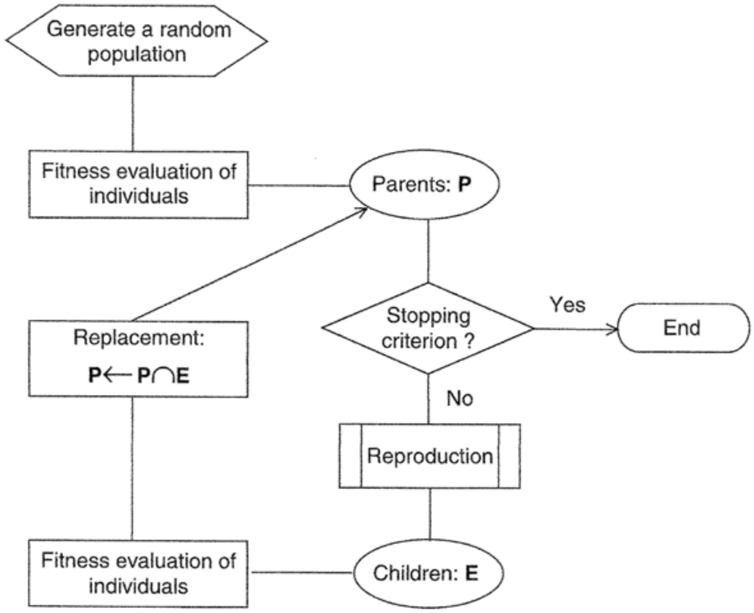

Figure 11. Flow Chart of a GA. From [27].

It is useful to mention some differences that GA has over traditional algorithms highlighted by [16]. GA works with a discrete search space, even though the function may be continuous. That allows GA to be used in problems with discontinuous functions. GA works with a population of solutions, and it is more likely the expected solution to be a global one. No gradient or auxiliary problem information is needed as it is only the objective function values that are used. Genetic algorithms use an initial random population and probabilistic rules to guide their search, help them recover from early mistakes and handle a wide range of problems. Furthermore, by using various operators, GA can take advantage of parallel computing to reduce the overall computation time. A comprehensive study of genetic algorithms is presented in [28].

GA has been used both in single-objective and multi-objective optimization. Fonseca and Fleming [29] have divided multi-objective GA in non-Pareto and Pareto based approaches. The major advantage of GA is that it has a high probability of locating the global optimum. The main drawback, inherent in all EMO algorithms, is that they can be computationally expensive. Srinivas and Deb [30] proposed the non-dominated sorting genetic algorithm (NSGA), which is based on layers of classifications of the individuals.

The population is ranked on the basis of domination and all non-dominated individuals are classified into one category. The general flow chart of that approach is shown in Figure 12.

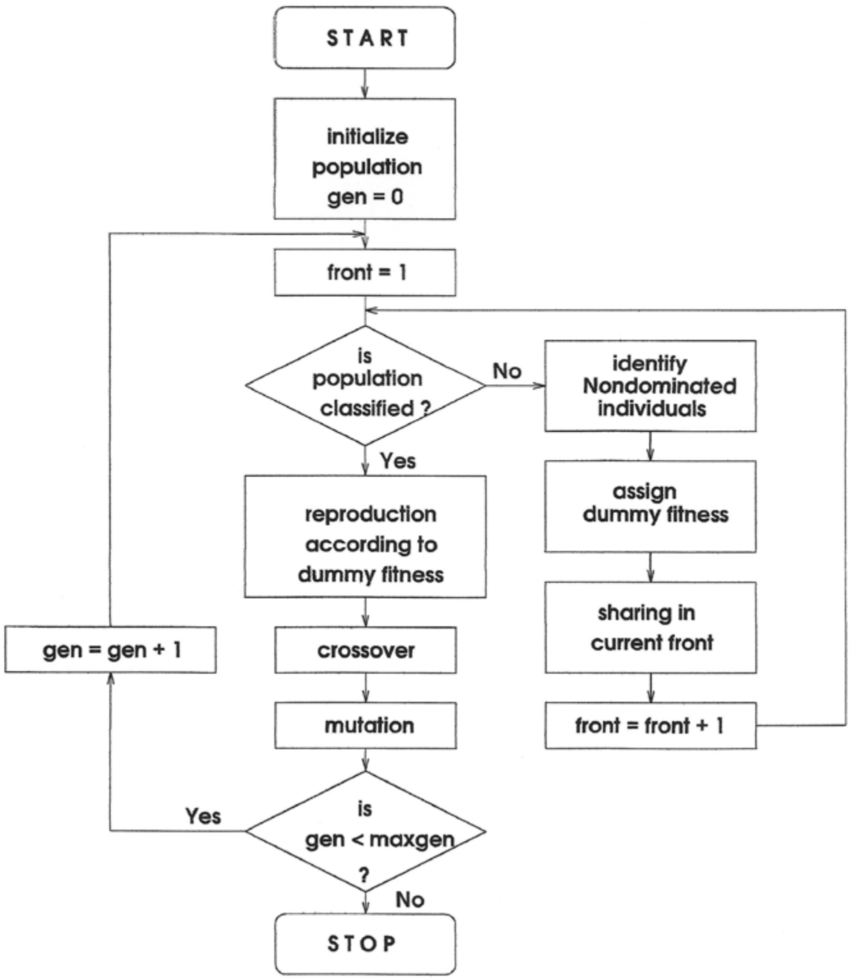

Figure 12. Flow Chart of the NSGA. From [30].

Deb at al. [31] proposed a new version called NSGA-II, which is more efficient and uses the concept of elitism, which keeps the best individuals from the parent and the child population. The multi-objective GA function gamultiobj of Matlab uses a controlled elitist genetic algorithm (a variant of NSGA-II) [32]. Elitist GAs favor individuals with better fitness value (rank) whereas, controlled elitist GAs also favor individuals that can help increase the diversity of the population even if they have a lower fitness value. The

initial population is generated randomly by default. The next generation of the population is computed using the non-dominated rank and a distance measure of the individuals in the current generation. Figure 13 shows a flow chart of that algorithm. An improved NSGA-II, called NSGA-IIa, has been proposed by [33] and another variant from [34] called NSGA-IIb. The new approaches have not been extensively tested yet, to the author's knowledge.

The particle swarm optimization (PSO) is another EMO and a population based stochastic optimization technique developed in 1995 by Eberhart and Kennedy [35]. The algorithm starts with a group of a randomly generated population and updates the population and searches for the optimum with random techniques. However, it does not guarantee success as it may get stuck in local optimums. PSO is easy to implement and there are few parameters to adjust. All the particles tend to converge to the best solution quickly, even in the local version, in most cases. A thorough description of particle swarm optimization is given in [36].

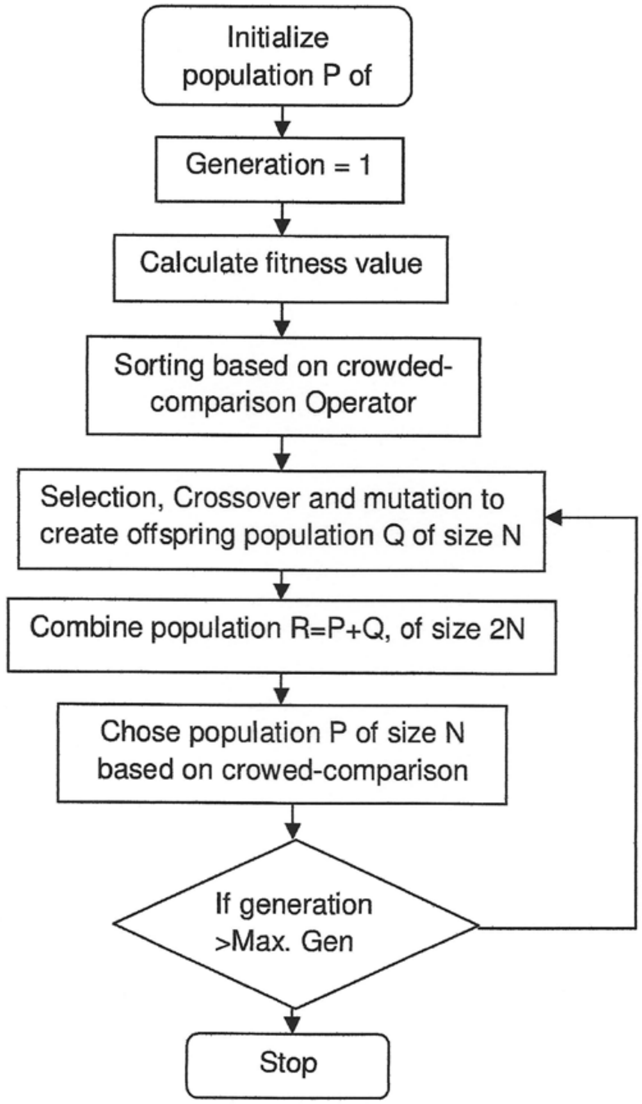

Figure 13. Flow chart for the NSGA-II algorithm. From [37].

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IV. AUTONOMOUS UNDERWATER VEHICLE CASE STUDY

A. OVERVIEW

The question is how one would design an AUV. The answer to that question is by meeting the requirements; that is, meeting the needs of the mission. Various payload configurations, depth ratings and endurances will be taken into account before the last decisions are made. There are two ways of tackling this problem. One approach is to optimize the model to meet the requirements at the feasible region of the design space, and the other one is to use modular design that permits reconfiguration of the vehicle for different applications. I use the first approach as the modular design is out of the scope of this thesis.

The main characteristics that determine the design of an AUV are the payload, the depth, the speed and the range at which it will operate. After determining those characteristics, the designer has the basic information to define and optimize the size, weight and power requirements of the AUV. One of the major characteristics of an AUV is the depth at which it will operate. The pressure to which an AUV is subjected increases linearly with depth. Roughly speaking, each 10 m of depth increases pressure by one atmosphere (14.7 psi). Thus, at 600 meters below the surface the pressure is about 60 times the atmospheric pressure, or 882 psi. The form of the hull and the pressure that this hull will tolerate must be considered first. There are a number of different ways in which hull design can be approached. Some aspects that must be considered during hull design are depth of operation, structural integrity for additions and tapings, impact conditions, water permeability, accessibility, versatility, future additions, size requirements, corrosion and chemical resistance.

In this case study three objective functions were evaluated that form a multi-objective problem. One of the goals is to minimize the power needed to overcome the resistance of the hull and provide the "hotel load," a term which will be explained subsequently. The other goals include maximizing the weight of the battery or any other energy-providing means compartment and maximizing the range of the AUV.

B. AUV MODEL

1. Hull Geometry

Pressure hull is a critical part of the design as it is the main load bearing structure of the AUV. It enables the AUV to withstand sea pressure as it descends into the water. Due to its nature the pressure hull is usually considered as a thin-walled curved structure. Moreover, the hull should be weight-efficient and its form should contribute to a low-drag vehicle design. The depth influences the size and the range of the vehicle. Going deeper tends to reduce the AUV's range and payload capacity. At the same time, the need to descend deeper increases the AUV's size and weight, mainly because the pressure hull should be thicker and heavier, leaving less residual buoyancy to support payload.

Even though a sphere is a good shape for withstanding pressure, there is the stability issue that makes it unusable [38]. A circular cylindrical hull is a good shape to resist the pressure [39] and most of the current AUVs have a circular cylindrical hull, including the most popular in military and scientific use, REMUS. Hsu et al. [40] give a detailed description of the hull stress concentration effect for deep-diving submersible vehicles.

There are two main hull forms that can be used in the design of an underwater vehicle and specifically an AUV. The one is the Carmichael hull, developed and tested by Dr. Bruce Carmichael of Rockwell International in the 1970s, which promotes laminar flow within the boundary layer. Regarding drag reduction, laminar flow is preferred to a turbulent boundary layer, because the skin friction is much lower. In a turbulent boundary layer the fluid particles move erratically causing higher shear stresses between layers and the surface [41]. The second choice is the cylindrical hull or 'torpedo body' hull, which has a nose cap followed by a parallel mid-section and a tail section. It has been the form choice for torpedo and submarine designers for a very long time (Figure 14). The advantages of the torpedo body hull are modularity, ease in launch and recovery, better hydrodynamic form than a spherical form of the same volume and low speed stability [39]. Even so, Paster [38] states that cavitation is one of the disadvantages of a cylindrical hull. Cavitation is a well-known phenomenon caused by the pressure distribution

generated by the moving vehicle. The maximum rate of change in curvature of the body has the negative minimum pressure. The water will start to boil when this pressure reaches the vapor pressure of water. These bubbles collapse when they reach the point where the pressure increases again and very high pressure is generated. This leads to high noise levels and the possibility of damaging the vehicle [38]. According to Paster, the nose of the circular cylinder used to be spherical, but this caused instability and cavitation. The shape of the nose was fine tuned to resemble the front of a teardrop. A good hydrodynamic body shape design will reduce the drag and improves the range of the vehicle by two to 10 times [38].

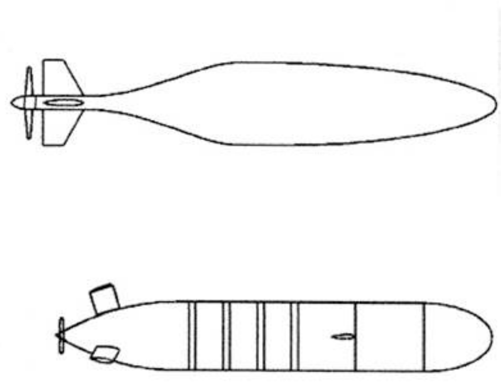


Figure 14. Example of Laminar Flow Hull and Torpedo Body. From [41].

In this work a torpedo body hull is used following the conceptual design phase prescribed in Jackson [42]. A summary of how the method, called the MIT method in the literature, was applied in the model is included for the purposes of identification and completeness. Design variables and parameters used in the model are summarized in Table 1.

Design Variable Definition			
Variable	Definition	Min	Max
D	Maximum hull diameter	0.1 m	1.5 m
$\mathbf{L_{tot}}$	Total Overall Length	0.6 m	9 m
$\boldsymbol{n_a}$	Aft form factor	1	6
$\boldsymbol{n_f}$	Forward form factor	1	6
V	Vehicle Speed	0.5 m/sec	3.1 m/sec
Parameter Definition			
Parameter	Definition	Value	
ρ	Seawater density	1025 kg/m^3	
ν	Kinematic viscosity	$1.05*10^{-6}$ m^2/s	
$\mathbf{c_a}$	Hull roughness coefficient	0.0004	
$\mathbf{V_{max}}$	Maximum speed	2.1 m/sec	
n	Discretization of hull	1000	

Table 1. Design Variables – Parameters Definition.

The hydrodynamic hull is broken up into three sections (Figure 15): the aft section, the forward section, and the parallel body. L_f is the length of forward part, L_a is the length of the aft part and the L_{pmb} is the length of the parallel body. L_{tot} is the total overall length of the hull. First, body plans are generated by calculating the location of each point on the hull as described in the following paragraphs.

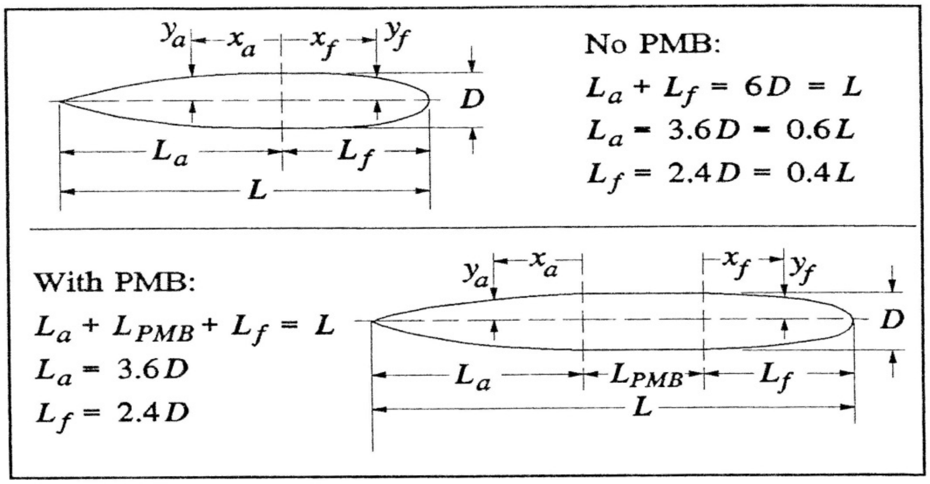


Figure 15. Geometry of a Torpedo Body Hull. From [42].

$$L_f = 2.4D$$
$$L_a = 3.6D$$
$$L_{tot} = L_f + L_a + L_{pmb}$$
$$\delta x = \frac{L_{tot}}{n}$$
$$i = 0...n$$
$$x_i = i(\delta x)$$

I divide the length of the hull by n where $n = 1000$ and x_i is the actual longitudinal location of each point. In this case y_i is the i_{th} transverse location of the hull.

$$y_f = \frac{D}{2}\left[1 - \left(\frac{L_f - x_i}{L_f}\right)^{n_f}\right]^{\frac{1}{nf}} \quad where \quad x_i = 0...L_f$$
$$y_{pmb} = \frac{D}{2} \quad where \quad x_i = L_f...L_f + L_{pmb}$$
$$y_a = \frac{D}{2}\left[1 - \left(\frac{x_i - L_f - L_{pmb}}{L_a}\right)^{n_a}\right] \quad where \quad x_i = L_f + L_{pmb}...L_{tot}$$

For the wetted surface and the volume of the hull the formulas Jackson used are:

$$WS = \pi D^2\left[\frac{L}{D} - K2\right], \quad V = \pi\frac{D^3}{4}\left[\frac{L}{D} - K1\right],$$

where L/D is the length-to-diameter ratio and $K2$ is a function of n_a and n_f which is calculated using a formula or tabulated data (Figure 16). In this thesis, the wetted surface is calculated using Matlab both by integrating the formula: $A = 2\pi rh$ with $r = y_i$ (1) and $h = 0...L_f$ and by using trapezoidal rule (command trapz in Matlab) (Appendix A). The same applies for calculation of the volume of the hull using: $V = \pi r^2 h$.

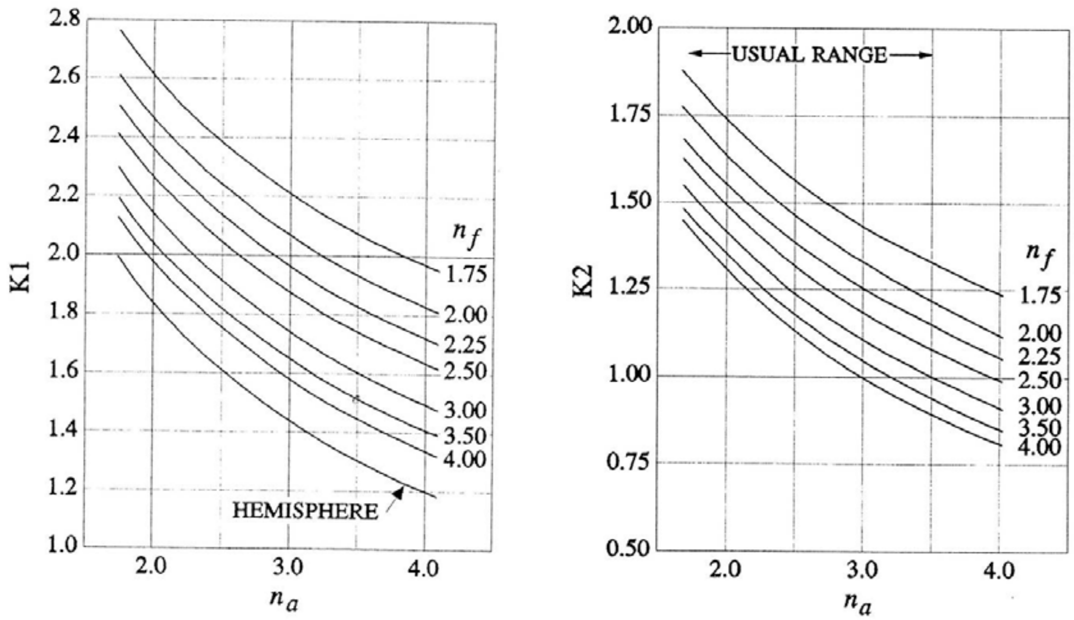


Figure 16. Parameters K1 and K2 as a Function of n_a and n_f. From [42].

There are two kinds of drag an underwater vehicle encounters, one from the normal forces and one from tangential forces (form drag and skin friction drag). As the L/D ratio increases, the body becomes longer and more slender and the pressure drag decreases. The skin friction drag is proportional to the wetted surface. A long vehicle would have more wetted surface than a short fat one of the same displacement. Figure 17 shows the variation of the two kinds of drag and their summation plotted against the L/D ratio for constant volume. There is no precise minimum, and therefore, there is some disagreement in the literature about the 'ideal' L/D ratio where a value of six or seven is used. This work uses an L/D ratio of six.

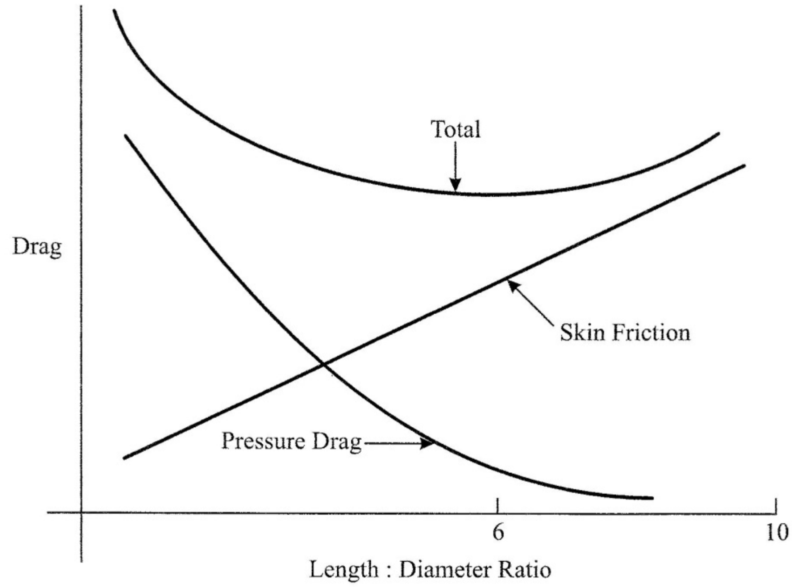


Figure 17. Drag Components for Constant Volume Form. From [43].

According to Jackson and many others in the literature, the ideal form needs a continuously changing diameter along the length of the vehicle. The ideal shape would have an elliptical bow and a parabolic stern [43]. Jackson states that the ideal submarine hull would be one with no parallel mid-body, and the sum of the aft and forward section length would be six times the maximum diameter. It is obvious that the number of scientific or military devices needed for the subsea vehicles nowadays has been increased considerably in order to meet the required operational capabilities. Thus, more volume is needed, and the designers inevitably stretch the hull by increasing the mid-body length. If a modest differentiation from the ideal is adopted, namely using a small portion of the parallel mid-body, that would result in an increase of the available volume and payload as well as in a reduction of the building costs without any severe drag and noise penalties. A great deviation from the ideal form, however, would increase the drag and the noise and consequently would affect maximum speed and range (Figure 18).

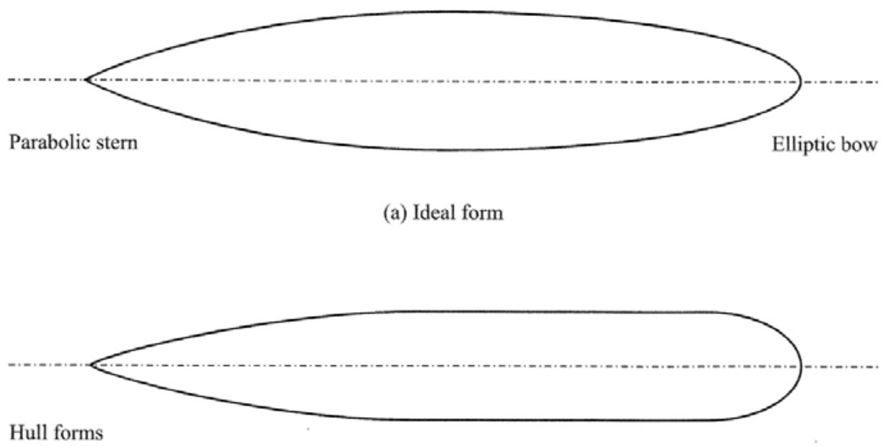


Figure 18. Hull forms. From [44].

2. Resistance – Power

When the AUV is moving at a constant speed, the thrust needed is equal to the drag of the vehicle. Drag force is one type of surface force encountered by any object traveling through water. The total drag on a body consists of a combination of pressure forces (form drag) and shear forces (skin friction drag). The form drag is due to the shape of the vehicle and long thin bodies typically have a lower form drag. The skin-friction drag is created due to the contact of the surface area of the body with the fluid. The goal for the designer is to minimize the total drag by finding the ideal body shape. As already mentioned, the contradiction between objectives may make the designer deviate from the optimum body shape if, for example, more internal volume is needed.

The total drag force or resistance of a submersible vehicle is:

$$R_t = \frac{1}{2} * \rho * \mathrm{V}_{\max}^2 * (\mathrm{WS} * (c_F * formfac + c_A + c_r) + R_{app})$$

I have not included the wave-making coefficient in the previous formula. It is widely accepted that a deeply submerged vehicle does not generate wave resistance. This coefficient applies only to conventional submarines which are required to travel close to the surface when snorkeling, resulting in the generation of surface waves.

There are various ways to calculate the coefficient of friction (c_F) in the literature. The one proposed by [42] is used here.

$$c_F = \frac{0.075}{\log_{10}(RE-2)^2} \quad \text{where} \quad RE = L_{tot} * \frac{V_{\max}}{\nu} \text{ (}RE\text{ is the Reynolds number)}$$

There are various ways to calculate the form factor (*formfac*) as well. I used the one proposed by Gillmer and Johnson [45].

$$formfac = 1 + 0.5 * \frac{D}{L_{tot}} + 3 * \left(\frac{D}{L_{tot}}\right)^3$$

c_A is usually called the roughness correlation allowance coefficient. It is a coefficient for the resistance caused by hull openings, fouling of the hull and so forth. The value ranges from 0.0003 to 0.0012 and a typical value of 0.0004 is used in this model. c_r accounts for the pressure difference along the hull while it is moving. Designers usually take it into account for high-speed submersibles and into submarine design. I will consider c_r as negligible in this case. R_{app} accounts for discontinuities, control surfaces, and other appendages that increase the total drag. Manufacturers try to make the surface as smooth as possible and create a smooth transition into the main body in order to minimize their contribution to the total drag. For concept designs a value of 1/1000 of the product of the total length and diameter of the hull is assumed for the appendage resistance, notwithstanding.

Knowing the total resistance, one can calculate the effective horsepower, EHP, needed to propel the hull of the AUV at a given speed.

$$EHP = R_t * V_{\max}$$

The first objective of this multi-objective optimization problem is to minimize the resistance of the AUV hull and consequently to minimize the effective horsepower.

3. Payload

Payload is the most important part of the vehicle. It includes science sensors, sonar electronics, data transfer devices or anything that the vehicle would carry to fulfill its mission. I could have used the maximization of the payload of the vehicle through maximizing the volume as one of the objectives. I assumed, however, that for a practical design specific operational requirements are more likely to exist, and therefore, the payload weight would be given. Thus, in this model the payload weight $W_{payload}$ is taken to be 40% of the total weight.

AUVs are typically designed to operate at neutral or near-neutral buoyancy and a fixed ballast system is used to achieve the proper trim condition. Additionally, they are equipped with an emergency drop weight system to bring the vehicle to the surface if the propulsion or control system fails. During ascent-descent movement or salinity changes, on-board variable ballast tanks are used together with compressed air systems to fill and empty the tanks with water. Therefore, designers calculate the total weight by multiplying the volume of the hull by its density, which must be equal to the density of the surrounding water (sea water in this case). I also assumed the weight of the machinery and propulsion (motor, propeller) W_{prop} and the weight of the appendages W_{append} to be 10% and 5% of the total weight, respectively. The weight of the hull W_{hull} is calculated by multiplying the difference of the outer and the inner volume of the hull by the density of the selected material. A hull thickness of 6mm is typically used for maximum depths of 600m. The second objective is to maximize the weight of the energy section of the vehicle and it is measured in kg.

$$W_{energy} = W_{tot} - W_{hull} - W_{prop} - W_{append} - W_{payload}$$

An important choice that needs to be made during the design phase is the kind of material that will be used for the hull. Steel has been used extensively in the past. Various materials have been proposed and some features that need to be taken into account are: high strength-to-weight ratio, affordability and corrosion resistance. Ross [39] compared four materials: titanium, high-strength steel, aluminum and composites.

The titanium alloy (Ti-6Al-4V) has a high cost, high strength, light weight and it is maintenance-free. The titanium alloy has the following characteristics: the specific gravity is 4.5 (kg/dm3); it has high corrosion resistance, low electric conductivity, low heat conductance, is not magnetized and has low workability [46]. The titanium alloy does not need the surface treatment even if it is used in the sea.

The high tensile strength steel has a moderate cost; it is heavy weight and requires surface treatment to use it in the sea. The specific gravity of the high tensile strength steel is about 7.9 (kg/dm3). The advantages of high strength steel are its moderate price and the fact that it is commonly used. The major disadvantage of steel is the low strength-to-weight ratio.

Aluminum is also widely available and it has a better strength-to-weight ratio than steel. The disadvantage of aluminum is its vulnerability to corrosion as it is anodic to most other structural alloys. It has a better strength-to-weight ratio of titanium, but it is an expensive material.

Glass-fiber reinforced plastic (GFRP) is the most commonly used composite for marine vehicles. The main advantages of GFRP are its price and a very high strength-to-weight ratio. Metal matrix composites (MMC) have several advantages over GFRP but are still in the development phase, making them very expensive (about 15 times more expensive than GFRP) [47]. Another material that can be used for AUVs is acrylic plastic. Table 2 summarizes the properties of some common materials that are used or can be used for the hull of an AUV. The specific strength is given by the ratio of the yield strength and the density. Figure 19 shows several AUV hull materials used in various depths.

Other alloys are under development to be used in new type pressure vessels with a goal of reducing the weight. Magnesium alloy and super carbon fiber are two examples. Many magnesium alloys have been developed lately as parts of cars, aircraft and mobile devices. The magnesium alloy is lightweight and its specific strength is very high. The specific gravity of the magnesium alloy is 1.8 (kg/dm3), which is about one-third that of

titanium or about two-thirds of aluminum [46]. This model lets the user select the material for the hull and I chose the aluminum for obtaining the values for this thesis.

Material	Density ($kg/dm3$)	Yield strength (MPa)	Tensile modulus (GPa)	Specific strength (kNm/kg)
High strength Steel (HY80)	7.86	550	207	70
Aluminum alloy(7075-6)	2.9	503	70	173
Titanium alloy (6-4 STOA)	4.5	830	120	184
GFRP (Epoxy/S-lass)	2.1	1200	65	571
CFRP (Epoxy/HS)	1.7	1200	210	706
MMC (6061 Al/SiC)	2.7	3000	140	1111
Acrylic	1.2	103	3.1	86
PVC	1.4	48	35	34

Table 2. Material Properties. From [47].

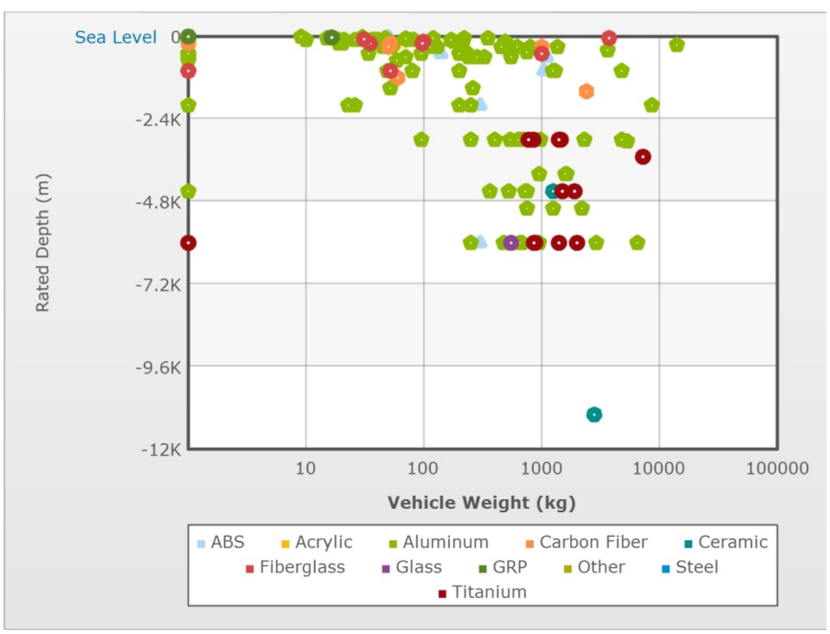


Figure 19. Various AUV Hull Materials. From [48].

4. Energy – Range

A critical part of the AUV design is the energy storage unit and its efficiency. Since I need to maximize the range of the AUV, a power source that can make it operate for a long period of time is needed. Thus, a power source with high-energy density and high-energy efficiency is an essential component of the vehicle.

Although prototype fuel cells, Stirling engines, CCDE (Closed Cycle Diesel Engines) and closed steam turbines have been developed and manufactured in recent years as underwater power sources, the most common power supply for AUVs is batteries. For more than 40 years low energy density batteries such as lead-acid and nickel-cadmium batteries have been used extensively. Another widely used power source in later years was the silver zinc battery which has high specific energy (130 Wh/kg) and density (240 Wh/lt). However, choices have changed recently due to the advantages offered by lithium-ion and lithium-polymer batteries [49]. Primary batteries (that is, batteries that are non-rechargeable) are available with specific energies to over 600 Wh/kg. High cost, nevertheless, makes their use justifiable only for very small vehicles or for special purpose missions. Manufacturers have widely used secondary batteries having the advantage of charging-recharging cycles and an energy density that comes up to 350 Wh/kg for the lithium ion batteries (Figure 20) [50]. Their relatively low price makes lithium batteries attractive for use in AUVs. They are not supposed, however, to reach a specific energy of 500 Wh.kg-1 for the next years, as described in the AEA Technology roadmap for AGM lithium ion 'D' cells out to 2020, with an improvement from ~7Ah in 2005 to ~17Ah in 2020 (equivalent to ~400 Wh/kg) [51].

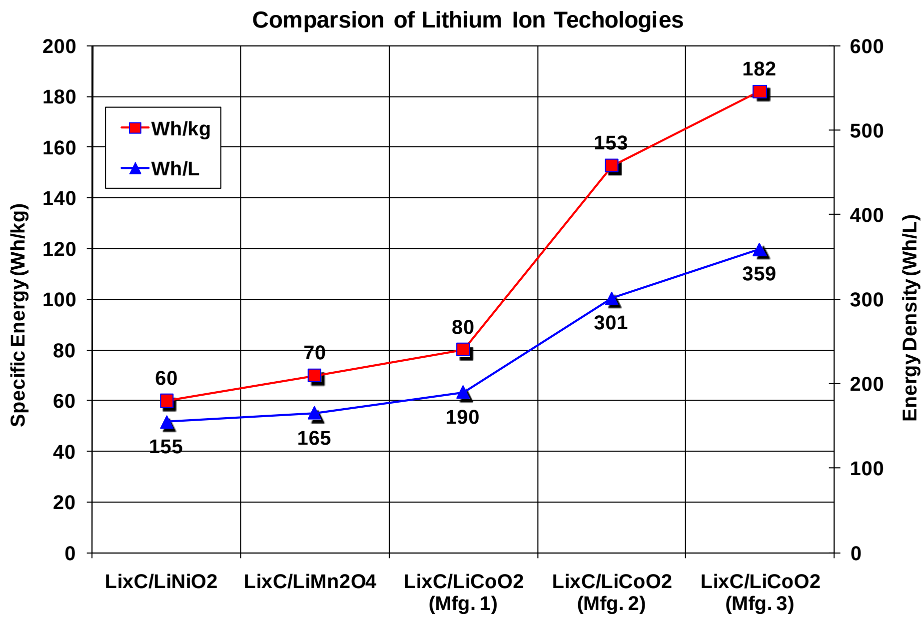


Figure 20. Comparison of Lithium Ion Batteries with Various Transition Metal Oxide Cathode Materials. From [50].

There are typically two types of loads, propulsion load and the non-propulsion load or "hotel load." Propulsion load includes propulsion and control surface actuator load, while the hotel load includes power consumption of the on-board computers, vehicle navigation sensors, and other auxiliary loads. In this model, I assume that specific operational requirements are given, and therefore, I can take the hotel load and the payload weight as given.

The fuel cell is considered to have been invented in 1839 by Sir William Grove, a British physicist, who was a pioneer of fuel cell technology. In a fuel cell, hydrogen and oxygen react electrochemically to produce electric power. Fuel cells change chemical energy directly into electric energy, and therefore, they have high energy efficiency.

Recently, the U.S. Navy has been heading towards power sources other than batteries, including fuel cells. In 2010, the U.S. Navy started a major multi-million dollar program for a long endurance Unmanned Underwater Vehicle (UUV). Ingenium was the prime contractor and the program started around October 2011. A second major new UUV program started in 2011 (for a large displacement UUV). In 2010 the Naval Undersea Warfare Center Division, Newport in Newport, R.I., awarded a sole-source

contract to Delphi to provide the 30-fuel cell Solid Oxide Fuel Cell (SOFC) system to power UUV applications [52].

In general, the fuel cell with hydrogen storage can provide far greater specific energy than rechargeable batteries, but has poorer specific power as shown in the Ragone plot of Figure 21. The poor specific power is mainly due to mass transfer limitations associated with the oxygen cathode [50]. There are five generic categories of practical fuel cells depending on the type of electrolyte used, including: phosphoric acid fuel cell (PAFC), proton exchange membrane fuel cell (PEMFC), molten carbonate fuel cell (MCFC), solid oxide fuel cell (SOFC) and direct and indirect methanol fuel cell (DMFC).

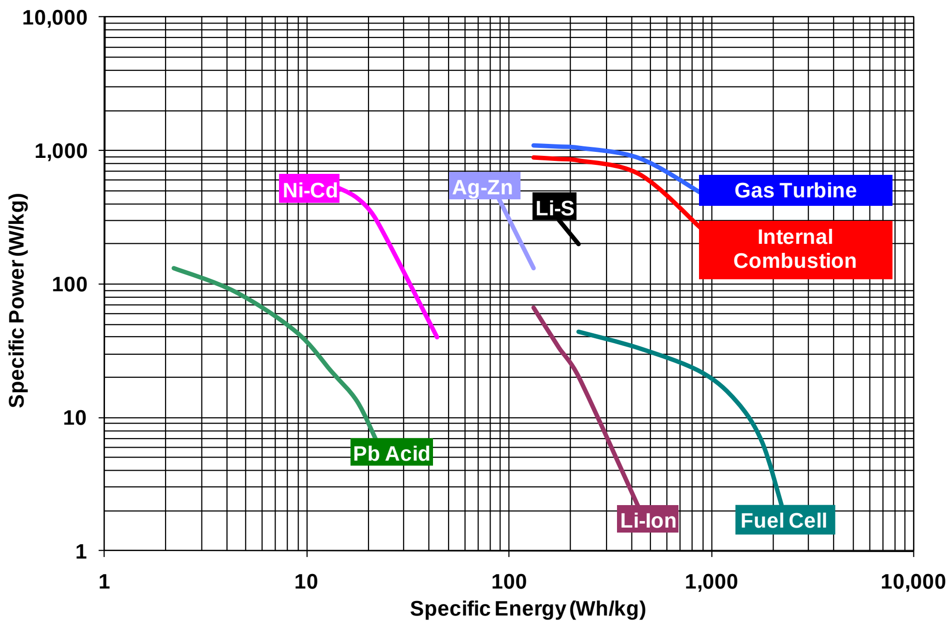


Figure 21. Specific Power vs. Specific Energy for Energy Conversion and Storage Systems. From [50].

While I will not discuss the differences of those types of fuel cells in depth, I will note that PEMFCs are smaller and have a lower operating temperature compared to the other types. Those are the main reasons that PEMFCs have been used in underwater vehicles as in the type 212a submarines built by HDW in Kiel, Germany, and the Japanese Urashima AUV that achieved the world's first and deepest AUV fuel cell power source dive in the summer of 2003 and completed an autonomous cruise of 220 km in the

spring of 2004 [53]. They are cells that operate on hydrogen and oxygen and are attractive power sources for AUVs because they are efficient, quiet, compact and easy to maintain. The total energy delivered by a fuel cell is limited only by the available fuel and oxygen stored onboard. The best combination for achieving the highest specific energy is using tanks to store liquid hydrogen and liquid oxygen as can be seen from Figure 22. Storing hydrogen as liquid, however, is assumed to be dangerous and so other forms are used. Type 212a German submarines use oxygen from cryogenic tanks and hydrogen from solid-state hydride canisters. Various oxygen storage options and their specific capacity/density are shown in Figure 23, where one can see that liquid oxygen has the highest volumetric and gravimetric density among the commercially available storage technologies.

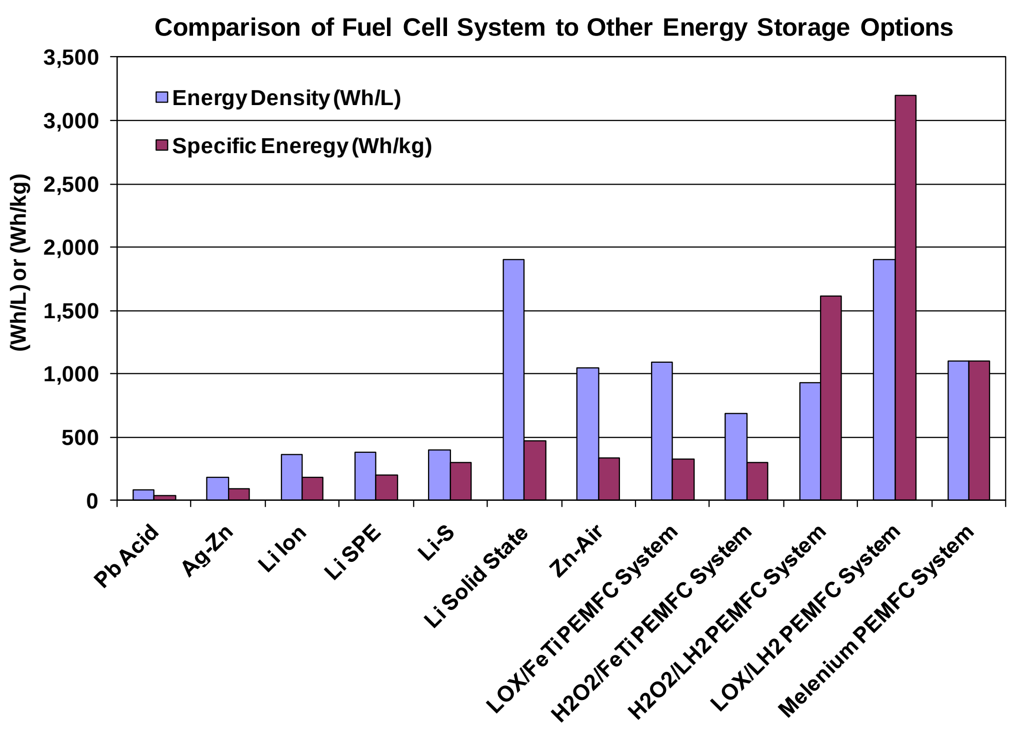


Figure 22. Comparison of Fuel Cell to Other Energy Storage Options. From [50].

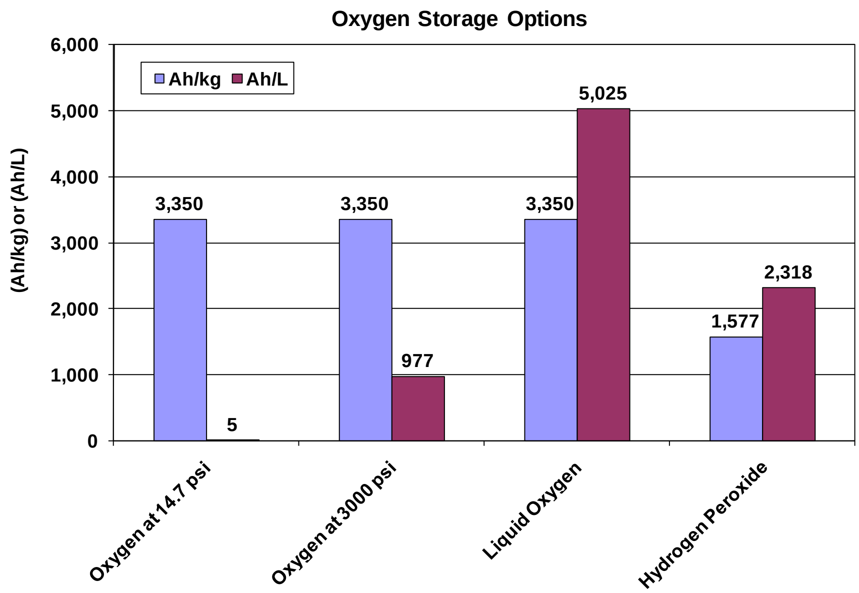


Figure 23. Various Oxygen Storage Options with Their "Equivalent" or "Apparent" Specific Capacity / Density. From [50].

From Figure 24 we can see that magnesium hydride has the highest storage capacity, even though it is not a practical solid-state storage medium yet [50]. The type 212a submarine uses the iron-titanium-hydride that has modest storage capacity, but is more easily handled.

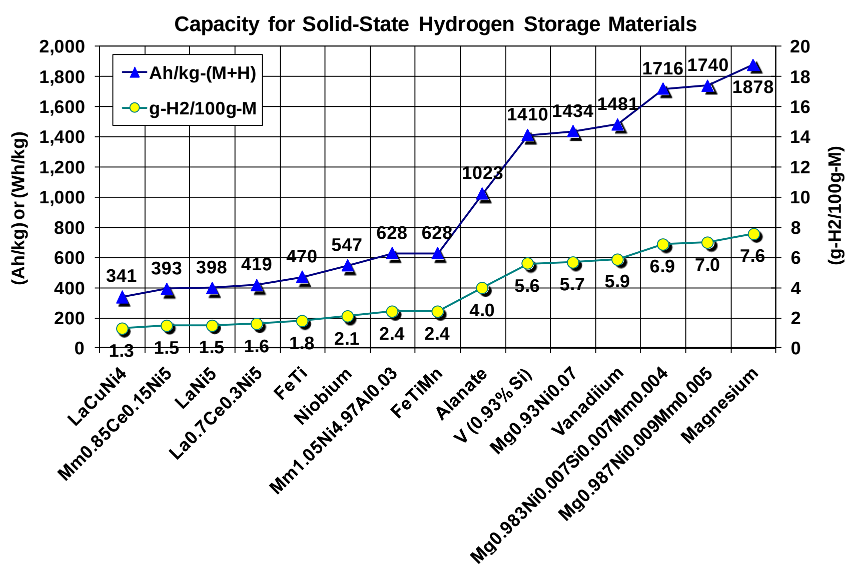


Figure 24. Range of Hydrides Available for the Solid-state Storage of Hydrogen for Underwater and Other Applications. From [50].

An alternative approach to using only fuel cells or batteries is to combine the two technologies within a hybrid system. Such systems have been proposed recently, combining the high energy density of the fuel cells with the high power density of the batteries and supercapacitors [54], [55]. The advantages of implementing such hybrid systems in underwater vehicles have been investigated in [51]. A simple illustration of a generic hybrid fuel cell power system, which shows the main components, is shown in Figure 25.

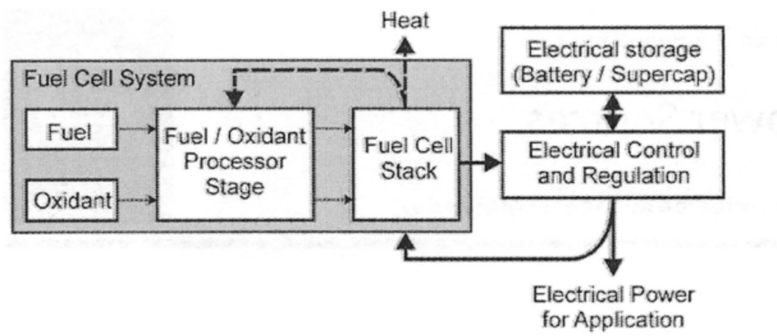


Figure 25. A Schematic Illustration of the Fuel Cell Hybrid Power System. From [56].

In a hybrid system, the fuel cell will provide a constant average power; that is, the power needed for overcoming the water resistance and some basic hotel load. The energy storage device (a secondary lithium-ion battery, for example) will provide the peak power in cases that this power is needed, namely for extra electronic devices like sonars or other scientific/military devices together with maneuvering and so forth. Furthermore, the battery will be recharged by the fuel cell during the low power demand period. A generic power profile is shown in Figure 26, where t_1 is the discharge time of the battery, t_2 is the recharge time, P_1 is the peak power and P_2 is the base power. The number of cycles determines the mission length of the AUV. The goal in this model is to maximize the range (that is, the number of those activity cycles).

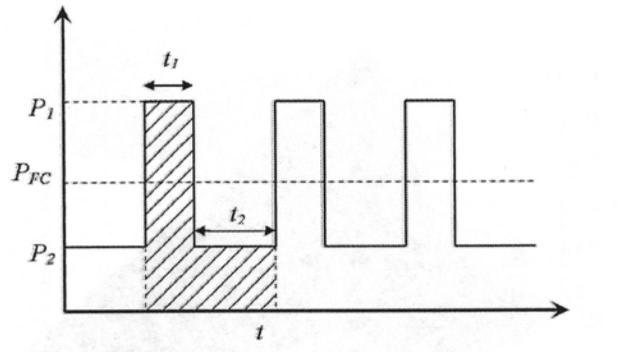


Figure 26. A Generic Power Profile for an AUV Mission. From [56].

The total available energy (E_{tot}) is the product of the weight of the energy section of the vehicle and the energy density of the power supply itself. For the hybrid system in this model, a specific energy of 500 Wh/kg is assumed, a realistic value for a hybrid system [51]. E_{tot} is also the product of the total power consumed and the duration of the mission. The total power consumed is the sum of the power consumed by the propulsion system and the hotel load. The power consumed by the propulsion system is equal to the effective horse power that we already know, EHP, divided by the overall efficiency/propulsive coefficient, PC that I will describe next.

$$E_{tot} = \left(\frac{R_t}{PC} + HL \right) * Duration \quad \text{or} \quad Duration = \frac{E_{tot}}{\left(\frac{R_t}{PC} + HL \right)}$$

The most common form of propulsion in AUVs is the screw propeller, although other propulsors have been used, such as the pump-jet propulsion system, the dual propeller-counter rotating thrusters or the special case glider/buoyancy-driven AUVs. I assume that a screw propeller is used in this model. The hub driven propeller is often used fitted onto the shaft of an electric motor. Both the motor and the propeller should transfer the power as efficiently as possible, yet several losses exist throughout that transfer. If *THP* is the thrust horsepower, that is, the product of the thrust delivered by the propeller and the vehicle speed, then:

$$EHP = \frac{(1-t)}{(1-w)} THP \quad [57]$$

The term $\frac{(1-t)}{(1-w)}$ is known as the hull efficiency η_H, t is the thrust deduction coefficient that is defined as: $t = \frac{T - R_t}{T}$, where T is the thrust delivered by the propeller and R_t is the total resistance. The wake fraction w is the ratio of the speed of the water in the wake of the hull or speed of advance, V_A, divided by the hull speed V: $w = \frac{V - V_A}{V}$

For a well-designed stern and propeller the hull efficiency is approximately equal to 1.0 [57]. There are cases, nevertheless, in which the hull efficiency can be greater than 1.0 and it is not actually a true efficiency [57].

Except for hull efficiency, there is also the propeller efficiency η_p that has two components: the open water efficiency η_O and the relative rotative efficiency η_R. The open water efficiency is the ratio between the power developed by the thrust of the propeller and that absorbed by the propeller when operating in open water, and the relative rotative efficiency is the ratio between a propeller's efficiency attached to a hull and in open water. Typical values for η_O and η_R range from 0.55 to 0.85 and 0.95 to 1.0, respectively.

The machinery efficiency η_M is defined as the ratio of the power delivered to the propeller, propulsive horsepower (PHP), divided by the power delivered by the propulsion motor, shaft horsepower (SHP) (Figure 27). An AUV propulsion system designer can avoid a reduction gear by carefully choosing an appropriate motor in order to save on weight and system losses. For a submersible vehicle η_M ranges from 0.95 to 0.99 [57].

A combination of the aforementioned losses known as the propulsive coefficient, PC, is usually used.

$$PC = \eta_H \eta_R \eta_O \eta_M \quad \text{or} \quad PC = \frac{EHP}{SHP}$$

Common values of propulsive efficiency typically range from 0.55 to 0.85 [57]. I use a value of 0.65 in this model.

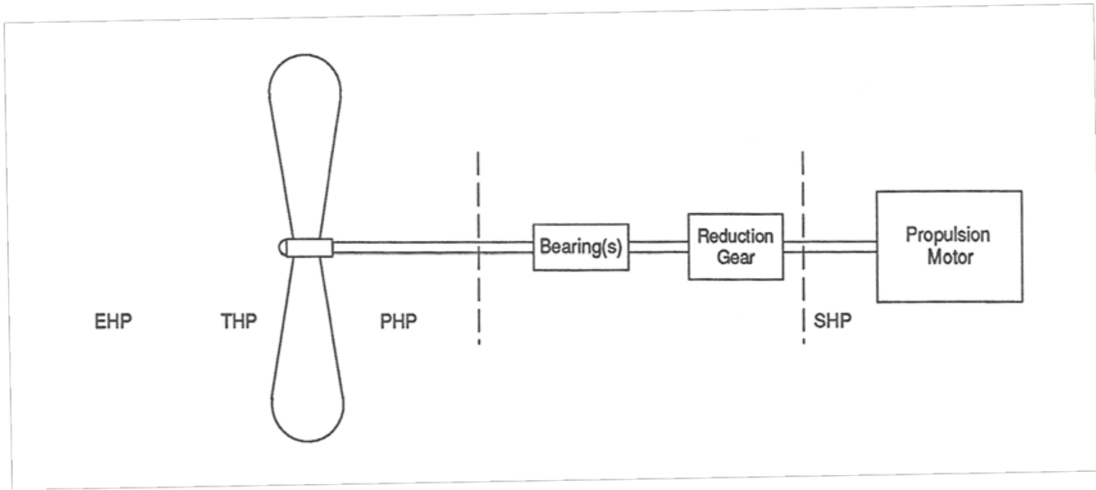


Figure 27. Propulsion System Efficiencies. From [57].

The range of the AUV at a speed V is measured in km and is given by the formula:

$$Range = Duration * V$$

By maximizing the range, the designer maximizes the number of activity cycles of the AUV mission as well.

5. Model Validation

In order to demonstrate the validity of the model's formulations, I will use an existing AUV design. The data gathering of existing AUVs, however, is not an easy task mainly because specific values needed, such as the form factors n_a, n_f, are not readily available in the literature. Moreover, regarding the range, I am assuming a constant speed for the mission and a specific energy of 500 Wh/kg that has not been implemented yet, and thus, there is no actual data I could use to compare.

I used a work done by Alvarez et al. [58] to validate the accuracy of the power section. In that work, which calculates the hull hydrodynamic optimization of AUVs, the Cormoran vehicle was considered. Cormoran is a surface layer AUV with a torpedo-like geometry defined by L_a=0.38m, L_f=0.24m, Radius=0.08m, n_a=3 and n_f=2.3. The theoretical values for resistance were validated experimentally in a ship model basin of

the University of Trieste in Italy [58]. Even though the numerical model of that work was found to underestimate the total resistance, the differences found between measured and computed values were not too big.

The values of this thesis' model were calculated using the Matlab functions surface_hull_2.m, volume_hull_2.m and power_auv.m found in Appendix A. The results of both models were compared and the agreement is very good as can be seen in Table 3, showing that the method was correctly implemented. A wave resistance component was added in the referenced work due to the fact that the vehicle was to move submerged near the free surface.

Inputs	**Reference values [58]**	**This Model's values**
n_a	3	3
n_f	2.3	2.3
Total length (m)	1.42	1.42
Radius (m)	0.08	0.08
Results		
Length of aft part, L_a (m)	0.38	0.576
Length of forward part, L_f (m)	0.24	0.384
Wet surface (m^2)	0.63	0.603
Volume (m^3)	0.0245	0.0221
Viscous resistance (N)	1.614	1.683
Wave resistance (N)	0.418	—
Total resistance (N)	2.03	—

Table 3. Model Validation by Comparing with Referenced Work.

A power system design based on the lightweight AUV US MARV used in [56] is an example of a real-world design that can validate the payload section of this thesis' model. The AUV model used in the referenced work is of a representative torpedo size with an external diameter of 0.324m, length of 3.76m and weight of 227kg with an aluminum hull. I did not have the form factor values of the referenced vehicle and typical values of n_a =2 and n_f =2 were used. The values of this thesis' model were calculated using the Matlab function weight_energy.m found in Appendix A. The results comparison can be seen in Table 4.

Inputs	**Reference values [56]**	**This Model's values**
n_a	—	2
n_f	—	2
Total length (m)	3.76	3.76
Diameter (m)	0.324	0.324
Results		
Total Weight (kg)	227	250
Payload (kg)	92.6	100
Payload Percentage (%)	40.8	40

Table 4. Model Validation by Comparing with Referenced Work.

C. OPTIMIZATION SETUP AND RESULTS

There are several commercial process integration and design optimization software packages to conduct optimization with multiple objectives. The Darwin optimization plug-in in Model Center version 7.1 was used in [59]. The parameter space investigation method implemented in a software package called MOVI (Multi-criteria Optimization and Vector Identification) was used in [60]. Particle swarm optimization as well as a comparison with other optimization techniques, like Monte Carlo and sequential

Monte Carlo, was demonstrated in [61]. Even statistical analysis software packages, such as JMP, have been used developing and analyzing the response surfaces as in [62], [63], [64], [65]. The previously mentioned works, however, used an extra tool for modeling and building the objectives, such as a ship synthesis model for naval crafts. In this work, the objective functions were built in Matlab and the global optimization toolbox of Matlab was used, specifically the multiobjective genetic algorithm solver, because of the great versatility it offers. Excel solver was used for two objectives to show how it works and compares with Matlab.

1. First Optimization Study

First, I try to find the Pareto front for two objectives. I have chosen the minimization of the power needed (EHP) and the maximization of the weight of the energy section of the vehicle. I use the Matlab files power_auv.m and weight_energy_auv.m, which are found in Appendix A, together with the Matlab optimization tool. I choose the gamultiobj function and a fitness function auv_multiobjective.m that consists of the two functions we need to optimize. Four variables are used: the diameter (D), the total length (L_{tot}), and the two sail form factors (n_f, n_a). I used two linear inequalities, $L/D \geq 6$ and $L/D \leq 9$, 6 for the 'ideal' L/D ratio and 9 as an upper bound for the mid-body section. The lower and upper bounds for the variables can be seen in Table 1 of this work. I used the default values for the various options that the tool gives, although user can change the population type and size, the selection function type, the crossover fraction, the mutation function, the migration type, the stopping criteria and so forth. The interested reader can find a thorough explanation of the various options in the Matlab documentation of the optimization tool. In Figure 28, we can see a screenshot of the Matlab optimization tool.

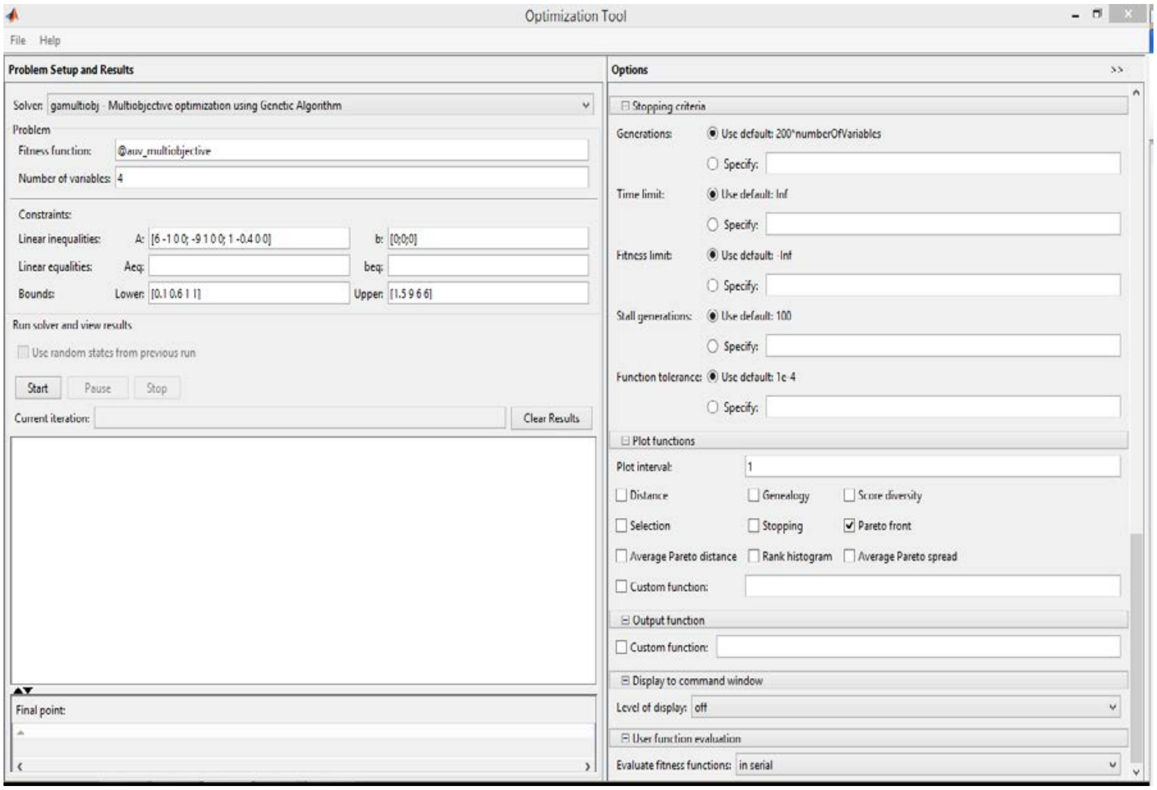


Figure 28. Matlab Optimization Tool with Two Objectives and Four Variables.

In Figure 29, we can see the Pareto front of the two objectives after running the solver and picking the Pareto front choice of the plot functions options. Users can also choose other plots of distance, genealogy, selection, average Pareto distance and average Pareto spread.

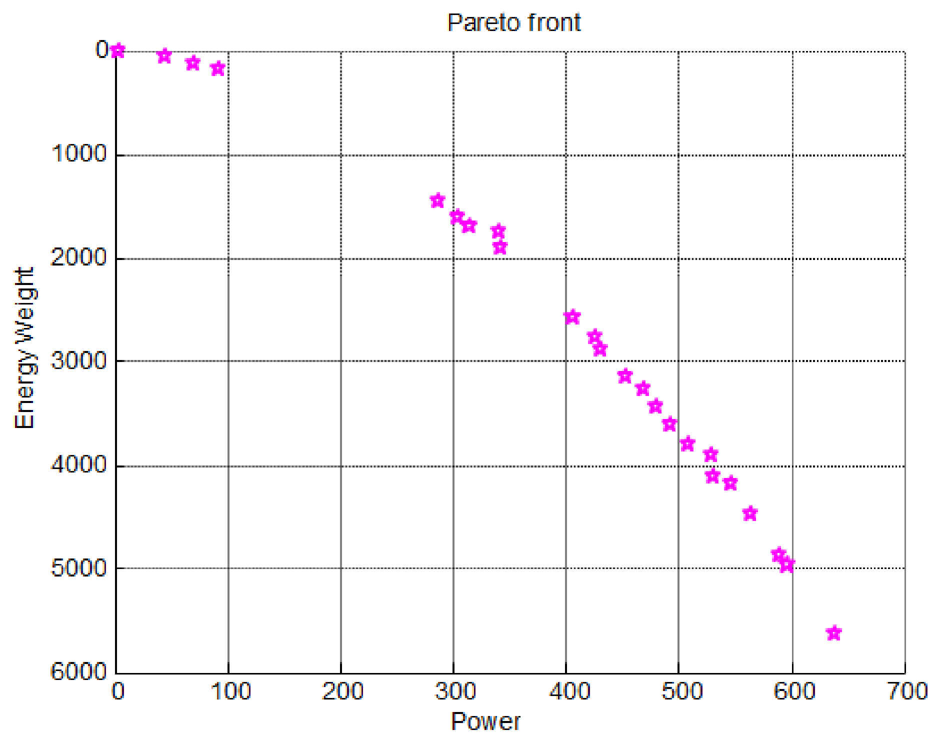


Figure 29. Matlab Pareto Front for Two Objectives Optimization Problem.

To better demonstrate the Pareto front utility I am introducing two additional points (Figure 30). Point A is a feasible point of the design space to the right of the Pareto front. Even though it is a feasible point, we can easily see that is dominated by two points of the Pareto front. One point located horizontally to A will have the same energy weight but a better (that is, lower) power and a point vertical to A will have the same power but a better (that is, higher) energy weight. The same applies for every feasible point to the right of the Pareto front. We can also see that even though point B dominates other points of the Pareto front, it is an infeasible point. That applies for all points to the left of the Pareto front. Thus, the only points that are worth considering by the design team are those of the Pareto front or Pareto efficient frontier, as it is sometimes called.

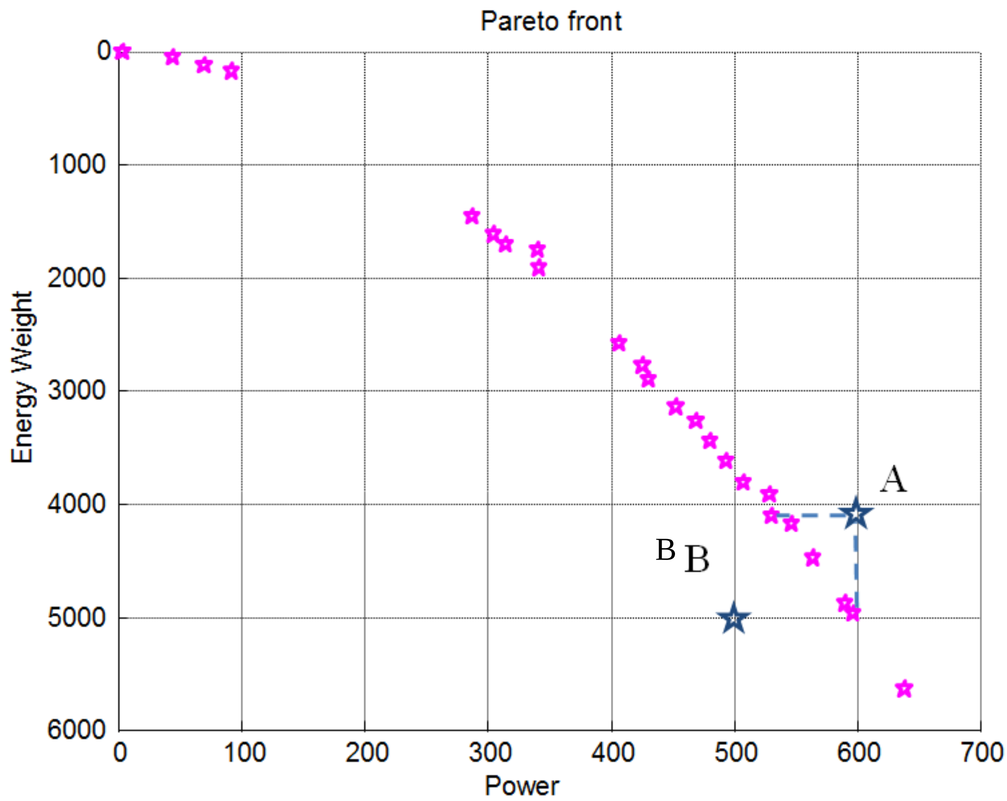


Figure 30. Matlab Pareto Front for Two Objectives and Two Additional Points.

One can also export the problem options and results to the Matlab workspace. The values of the variables and the objectives of this problem are shown in Table 5. I kept the speed constant with a value of 2.10 m/sec for this case. After obtaining the PO points the designer and the decision maker can analyze the interdependencies among decision variables and the objectives. They can use those points which dominate over all the others to get the best design. For example, a weight of 2584 kg of the energy section of the vehicle would give a value of 406 hp for the power needed.

EHP	Weight		D	L	nf	na
2.536	0.403		0.100	0.600	1.000	1.000
3.668	0.747		0.117	0.721	1.072	1.072
43.952	56.229		0.382	2.541	1.569	1.936
92.904	185.266		0.476	4.003	4.945	1.999
69.564	125.421		0.477	3.185	1.962	2.073
340.573	1759.256		0.927	7.700	4.760	4.778
287.336	1470.422		1.005	6.192	4.013	3.085
305.869	1623.421		1.016	6.333	4.789	3.837
342.606	1921.543		1.035	6.891	4.997	4.623
314.795	1707.808		1.056	6.646	3.610	2.708
406.925	2584.664		1.160	7.694	4.740	3.159
426.603	2787.971		1.180	7.722	3.410	5.051
469.563	3277.854		1.230	8.129	5.878	4.398
431.687	2902.007		1.243	7.607	2.930	4.376
453.455	3146.196		1.255	7.873	5.006	3.557
529.120	3915.689		1.264	8.917	5.929	4.977
481.002	3451.905		1.264	7.980	5.385	5.398
547.386	4189.013		1.311	8.879	4.657	5.629
493.792	3626.906		1.313	8.239	4.986	3.576
508.622	3808.853		1.337	8.256	3.585	4.661
532.101	4108.257		1.352	8.406	5.237	4.764
565.419	4480.576		1.358	8.843	5.341	5.407
590.873	4894.613		1.423	8.795	5.405	5.645
598.312	4977.250		1.423	8.920	5.405	5.645
639.843	5636.593		1.500	9.000	5.975	5.996

Table 5. Matlab Results for Two Objectives Optimization Problem.

The Excel solver does not have an option for multi-objective optimization but there are ways to circumvent that [66], even though multiple steps are required. First, I find the minimum and the maximum point for the weight of the energy section by using the solver and the same variables and constraints previously used in Matlab. Then I perform repeated optimizations on minimizing one of the two objectives—the power in this case—while increasingly constraining the weight for several values between the minimum and the maximum points. The model used in Excel and built by the author can be found in Appendix B. The values for the surface and the volumes needed were obtained by using Visual Basic in Excel and a function built to give the integral

numerically (Appendix B). The results and the plot acquired are shown in Table 6 and Figure 31. The similarity of the Excel and Matlab results in both the values and the plots is obvious.

W_power>	EHP	W_power	D	L	nf	na
0.44	2.533984	0.44037062	0.10	0.60	1.00	1.00
200	86.09805	200.143333	0.62	3.7	1.05	1.92
500	147.1993	497.341612	0.82	4.95	1.05	1.92
1000	223.9813	998.279654	1.03	6.19	1.05	1.92
1500	285.0312	1505.47083	1.18	7.05	1.05	1.92
2000	340.045	1998.86177	1.280	7.710	1.050	1.920
2500	395	2496.94947	1.38	8.28	1.05	1.92
3000	439.1169	3029.45478	1.45	8.97	1.05	1.92
3500	494.9336	3507.88383	1.27	9	3.38	2.59
4000	537.4575	3991.45585	1.27	9	5	5.5
4500	563.6612	4418.52691	1.33	9	5	5.5
5000	597.2013	5004.51886	1.41	9	5.39	5.65
5500	629.9659	5475.38121	1.49	8.95	5.78	5.7
5639	640.41	5639.12178	1.5	9	6	6

Table 6. Excel Solver Results for Two Objectives Optimization Problem.

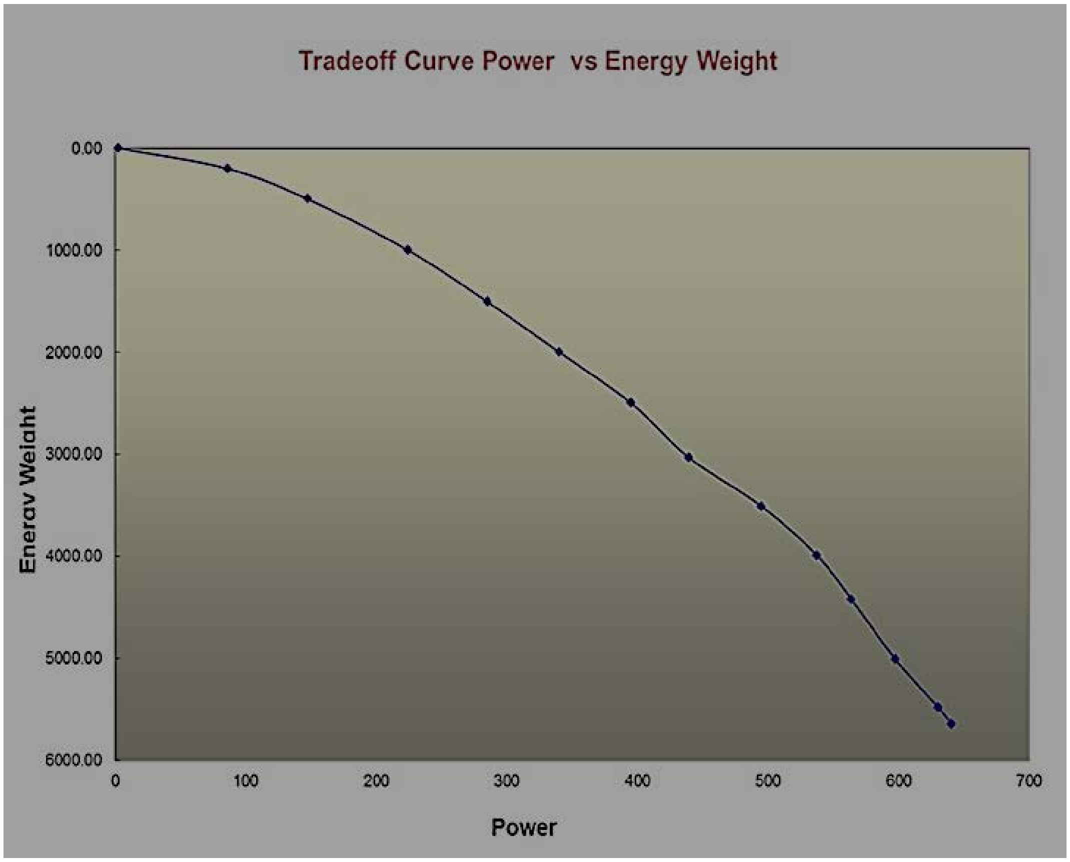


Figure 31. Excel Pareto Front for Two Objectives Optimization Problem.

2. Second Optimization Study

We can now proceed to an optimization case of three objectives. I choose the minimization of the power needed and the maximization of the weight of the energy section and the total range. I use the Matlab files power_auv.m, weight_energy_auv.m and the range_auv.m found in Appendix A. I choose the Matlab gamultiobj function and a fitness function auv_multiobjective.m with the same variables, the linear inequalities and the bounds used in the previous case. The speed remains constant with a value of 2.10 m/sec for this case as well.

After exporting the problem options and results to the Matlab workspace, I obtain the values shown in Table 7. Using the Matlab function gaplotpareto, I obtain the 3D plot shown in Figure 32. Matlab does not have an option for plotting three objectives and obtaining the 3D Pareto front. Figures 33 and 34 show the way to circumvent that.

EHP	Weight	Range		D	L	nf	na
2.536	0.403	2.472		0.100	0.600	1.000	1.000
57.946	78.996	425.189		0.381	2.847	4.435	3.536
116.194	289.387	1378.716		0.570	4.172	2.746	3.340
166.584	497.178	2154.636		0.612	5.384	4.420	5.585
191.269	648.248	2690.235		0.676	5.642	4.858	5.365
228.432	872.995	3405.585		0.734	6.344	4.598	4.796
200.282	794.313	3246.156		0.825	5.054	3.847	3.498
240.363	1050.619	4021.053		0.857	5.671	4.122	5.234
271.967	1342.692	4893.942		1.003	6.128	2.470	2.935
343.364	1934.375	6365.093		1.052	6.886	3.249	5.059
362.244	2171.335	6965.739		1.121	6.815	4.430	4.326
454.802	2964.767	8470.302		1.139	8.598	3.439	4.989
403.492	2528.892	7691.612		1.176	7.933	2.336	3.006
429.052	2828.894	8335.893		1.182	7.610	4.231	5.531
470.485	3347.545	9389.797		1.257	7.764	5.812	5.794
494.110	3565.546	9734.336		1.260	8.339	5.778	4.676
494.600	3650.460	9960.646		1.302	7.987	5.722	5.143
528.209	4029.095	10591.835		1.322	8.400	5.615	5.602
554.898	4390.443	11216.113		1.362	8.548	5.908	5.847
522.532	4014.861	10620.003		1.364	8.229	4.384	4.738
567.348	4611.952	11628.929		1.411	8.485	5.580	5.541
580.177	4762.377	11849.606		1.422	8.752	5.715	4.699
598.399	4990.711	12189.042		1.424	8.858	5.929	5.904
639.295	5628.646	13201.447		1.500	9.000	5.938	5.939

Table 7. Matlab Results for Three Objectives Optimization Problem.

We cannot see a knee-point in the plot of this optimization problem, so we have to consider all solutions equivalent to each other. It is up to the designer's preference or other given constraints to choose one of them.

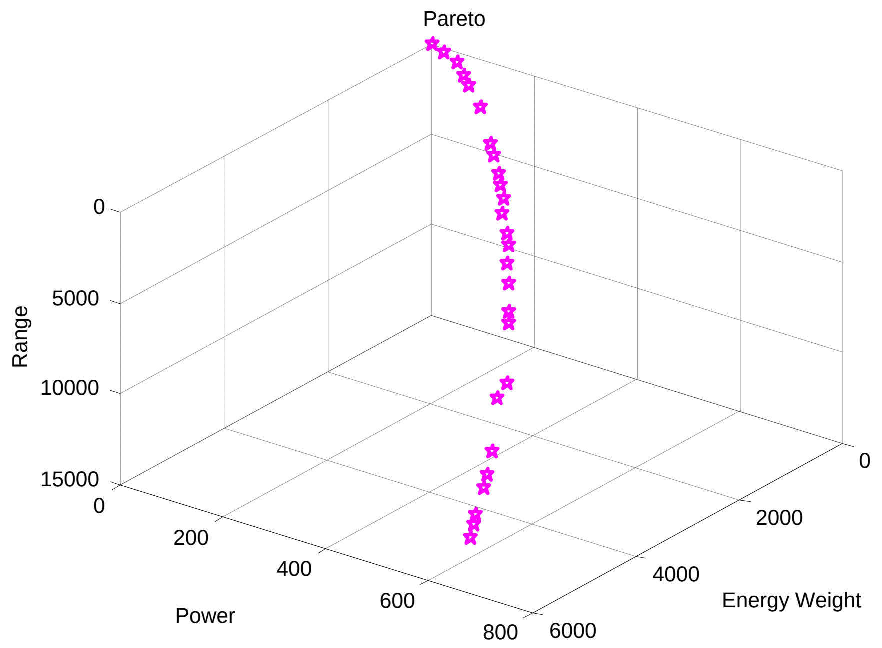


Figure 32. Matlab Pareto Front for Three Objectives Optimization Problem.

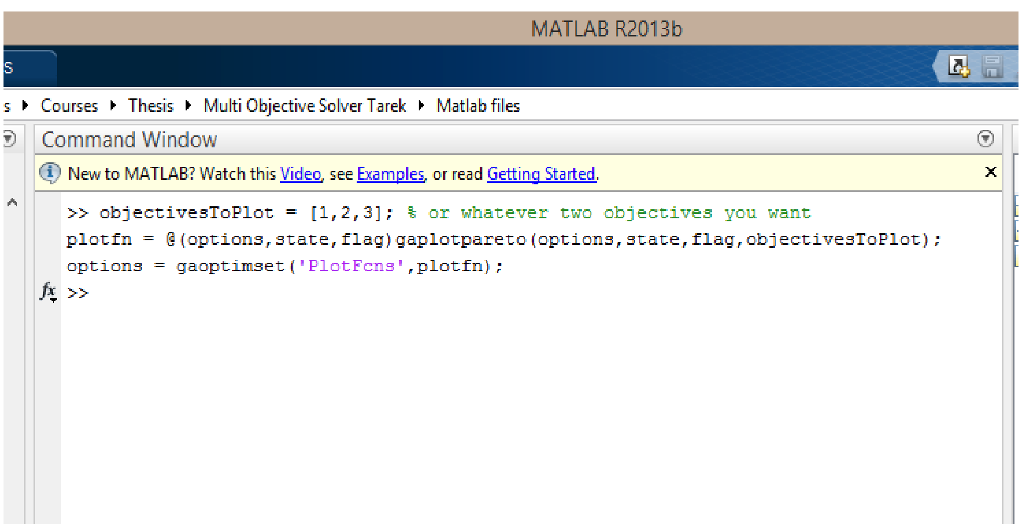


Figure 33. Matlab Commands for Plotting 3D Pareto Front.

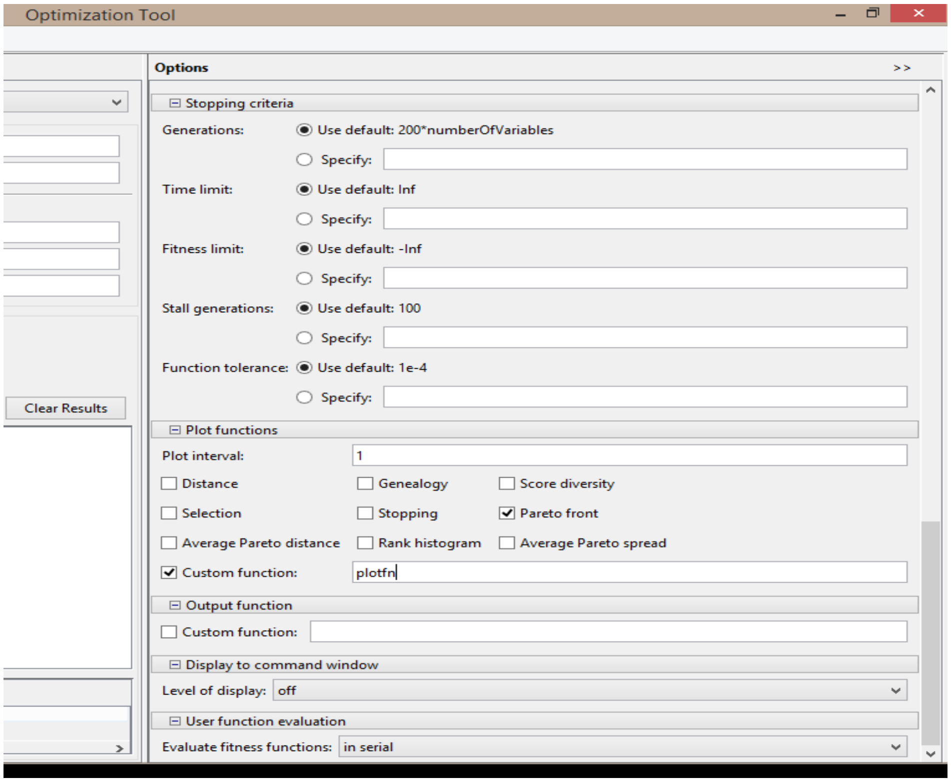


Figure 34. Matlab Optimization Tool Showing 3D Plot Function.

3. Third Optimization Study

In this case, the goal is to optimize the three objectives while having the speed of the vehicle as a variable. Thus, I use five variables, and the lower and upper bounds of the speed can be seen in Table 1 of this work. The obtained values of the variables and the objective functions can be seen in Table 8. In Figure 35, we can see the 3D plot of the three objectives, and in Figure 36, I show the 2D projection of the 3D plot. From the visual representation of the Pareto front one can clearly see the knee-point area.

Even though no one solution is better than any other solution in the PO front, a knee-point is a preferred solution, as mentioned before, and gives the designer a safe way to pick a single point in a trade-off front—or more if there is a knee-point area with multiple points. The designer needs to pay a high cost in either objective to have a minor gain in the other objective. Therefore, any movement away from the knee-point is not of great value and thus not preferred. As we can observe from the plot, we have to increase

the power too much to have a slight increase in the weight of the energy section, as we move further from the knee-point.

EHP	Weight	Range		D	L	nf	na	Velocity
0.049	0.410	0.618		0.100	0.603	1.003	1.002	0.502
0.049	0.411	0.616		0.101	0.603	1.003	1.002	0.500
2.260	149.669	263.392		0.475	3.594	3.265	1.493	0.590
5.465	810.469	1390.438		0.843	5.229	3.036	2.786	0.580
4.388	835.333	1324.571		0.866	5.211	2.979	2.669	0.534
6.007	1337.534	2136.381		0.975	6.086	3.594	2.991	0.541
6.120	1382.005	2206.428		0.984	6.144	3.624	3.017	0.541
7.282	1743.447	2807.870		1.044	6.677	3.797	3.203	0.547
7.972	2138.233	3423.292		1.178	7.092	3.928	2.005	0.545
8.812	2407.998	3877.093		1.184	7.127	3.801	3.363	0.549
10.034	2918.254	4692.961		1.221	7.871	3.861	3.479	0.550
10.743	3208.970	5182.647		1.266	7.913	4.461	3.660	0.553
11.995	3627.680	5906.520		1.291	8.286	4.671	4.343	0.559
16.588	4302.692	7488.580		1.357	8.743	4.822	4.651	0.605
19.749	4382.814	8033.311		1.385	8.618	4.880	4.524	0.642
20.745	4737.793	8673.920		1.428	8.868	4.636	4.190	0.643
24.321	5127.302	9678.338		1.450	8.961	5.194	5.215	0.668
30.526	5132.662	10333.239		1.451	8.976	4.664	5.410	0.723
84.065	5334.049	13495.746		1.475	8.961	5.224	5.499	1.025
40.378	5297.946	11434.104		1.476	8.981	5.211	5.077	0.794
63.363	5347.803	12813.696		1.488	8.977	5.004	4.937	0.928
96.521	5428.746	14004.334		1.492	8.979	5.174	5.250	1.072
116.846	5456.188	14429.563		1.492	8.994	5.217	5.330	1.145
150.175	5502.600	14886.141		1.499	8.997	5.215	5.301	1.248
203.959	5529.206	15126.490		1.499	8.998	5.226	5.490	1.388
168.872	5533.006	15056.229		1.500	9.000	5.228	5.494	1.299
212.519	5538.984	15149.010		1.500	9.000	5.228	5.516	1.407

Table 8. Results for Three Objectives Optimization Problem with Speed as a Variable.

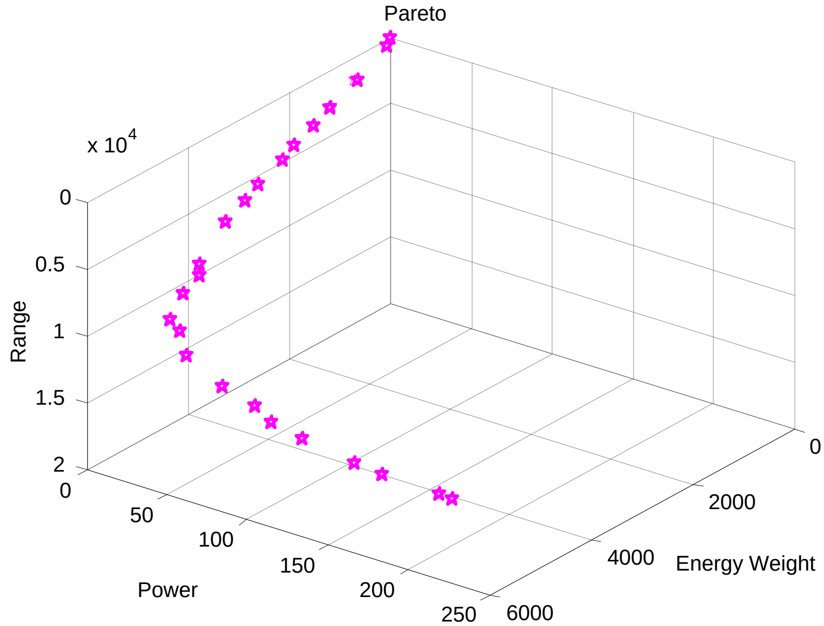


Figure 35. Matlab 3D Pareto Front for Three Objectives Optimization Problem with Speed as a Variable.

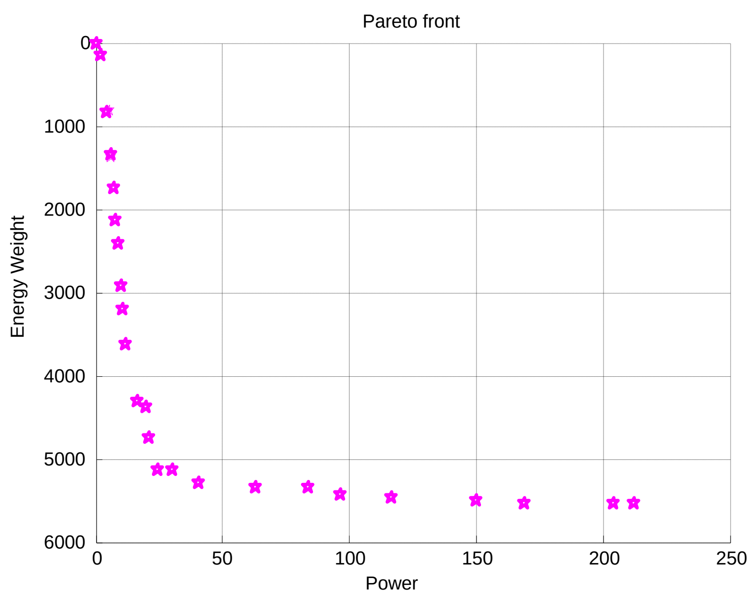


Figure 36. Matlab 2D Pareto Front for Three Objectives Optimization Problem with Speed as a Variable.

Even though all points are PO in the sense that they dominate all the others in the design space, the designer could safely pick the point with Power = 24.321 hp, Weight = 5127.302 kg and Range = 9678.338 km with parameter values shown in Table 6, as the best solution. If more knee-points were present, then again it would be up to the decision maker and his preferences or other constraints to decide which one to pick. Matlab does not have an option of plotting the surface of the Pareto front. The only way the author found is using linear interpolation. In Figures 37 and 38, I show two methods for obtaining the Pareto front surface using linear interpolation (rating the second as a preferred one) and in Figure 39, I show a surface plot of the Pareto front.

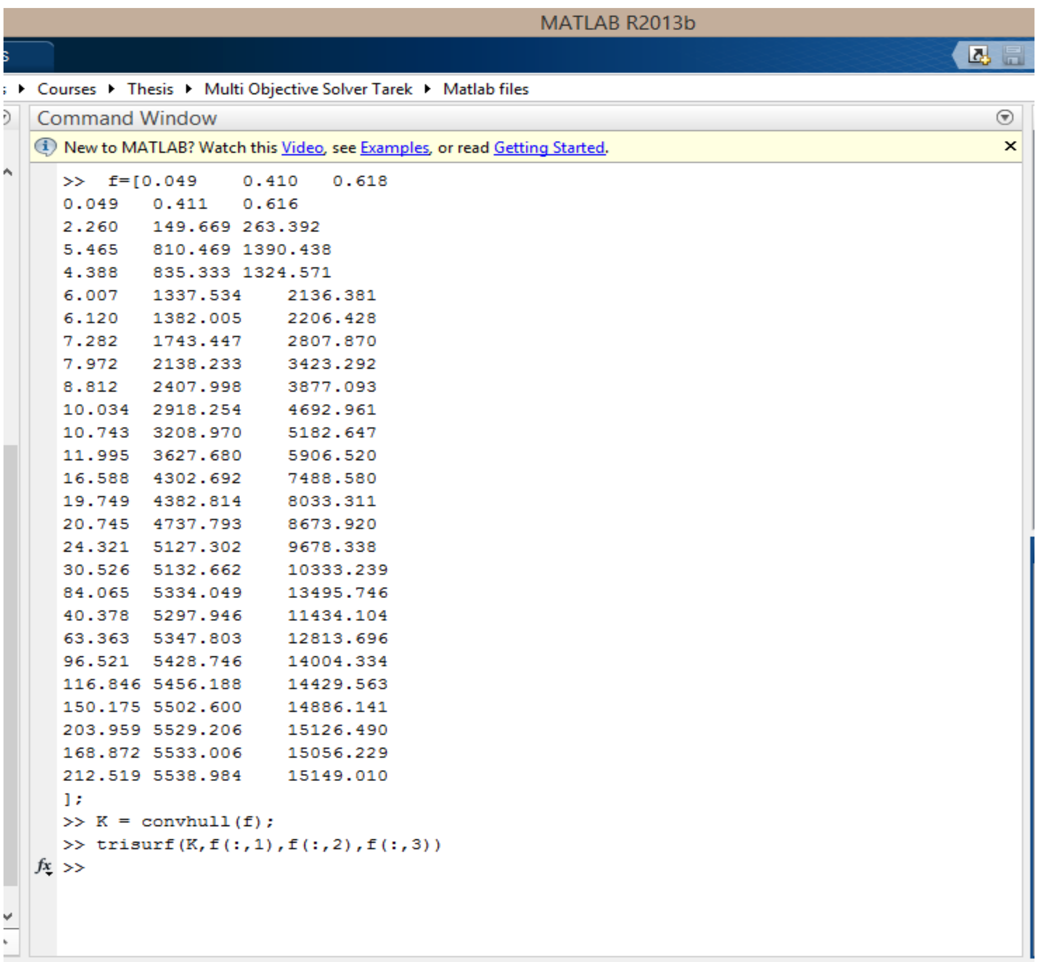
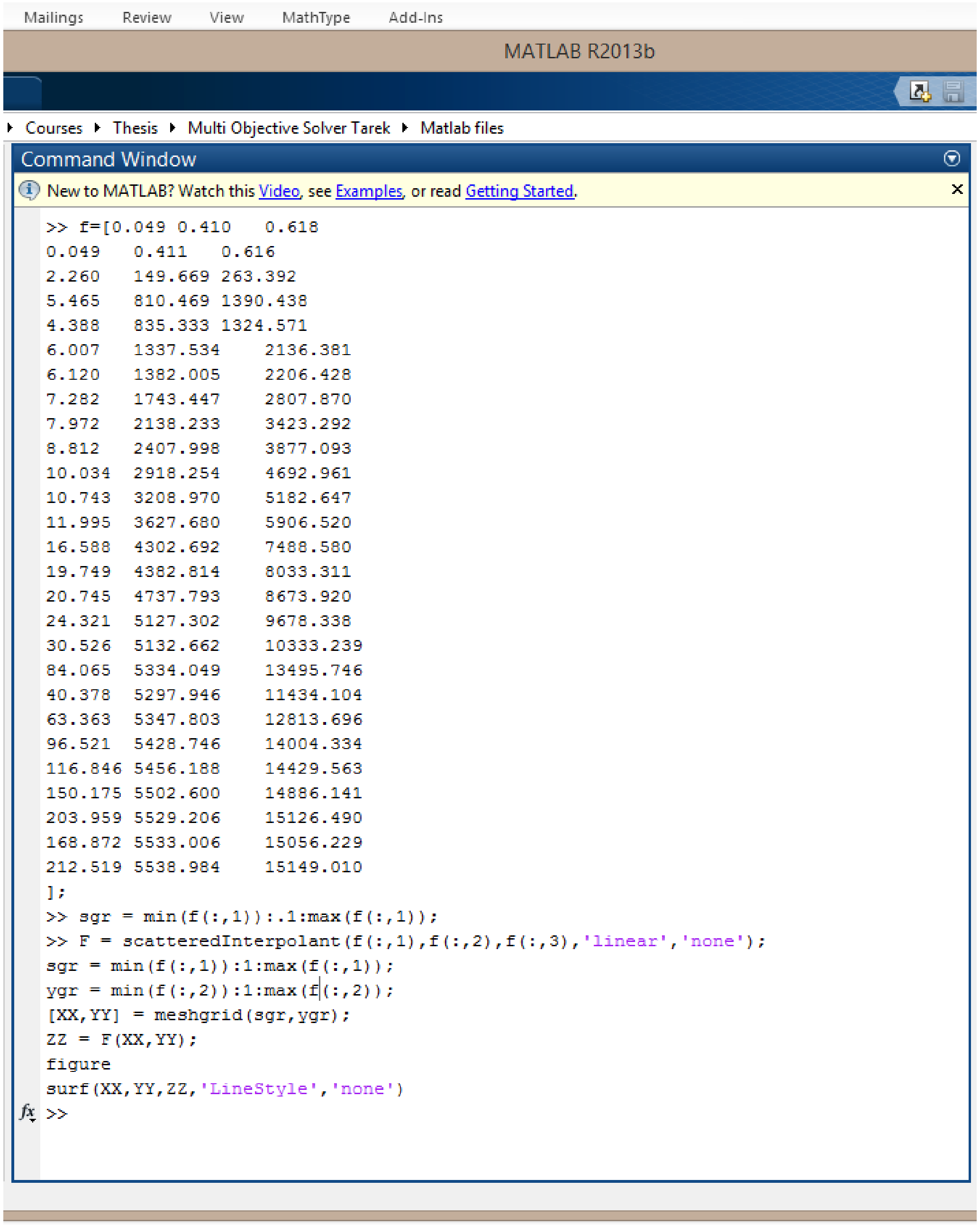


Figure 37. Matlab Commands for Obtaining the Surface of the Pareto Front (First Method).



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MATLAB R2013b

Courses ▸ Thesis ▸ Multi Objective Solver Tarek ▸ Matlab files

Command Window

New to MATLAB? Watch this Video, see Examples, or read Getting Started.

```
>> f=[0.049 0.410   0.618
0.049   0.411   0.616
2.260   149.669 263.392
5.465   810.469 1390.438
4.388   835.333 1324.571
6.007   1337.534    2136.381
6.120   1382.005    2206.428
7.282   1743.447    2807.870
7.972   2138.233    3423.292
8.812   2407.998    3877.093
10.034  2918.254    4692.961
10.743  3208.970    5182.647
11.995  3627.680    5906.520
16.588  4302.692    7488.580
19.749  4382.814    8033.311
20.745  4737.793    8673.920
24.321  5127.302    9678.338
30.526  5132.662    10333.239
84.065  5334.049    13495.746
40.378  5297.946    11434.104
63.363  5347.803    12813.696
96.521  5428.746    14004.334
116.846 5456.188    14429.563
150.175 5502.600    14886.141
203.959 5529.206    15126.490
168.872 5533.006    15056.229
212.519 5538.984    15149.010
];
>> sgr = min(f(:,1)):.1:max(f(:,1));
>> F = scatteredInterpolant(f(:,1),f(:,2),f(:,3),'linear','none');
sgr = min(f(:,1)):1:max(f(:,1));
ygr = min(f(:,2)):1:max(f(:,2));
[XX,YY] = meshgrid(sgr,ygr);
ZZ = F(XX,YY);
figure
surf(XX,YY,ZZ,'LineStyle','none')
>>
```

Figure 38. Matlab Commands for Obtaining the Surface of the Pareto Front (Second Method).

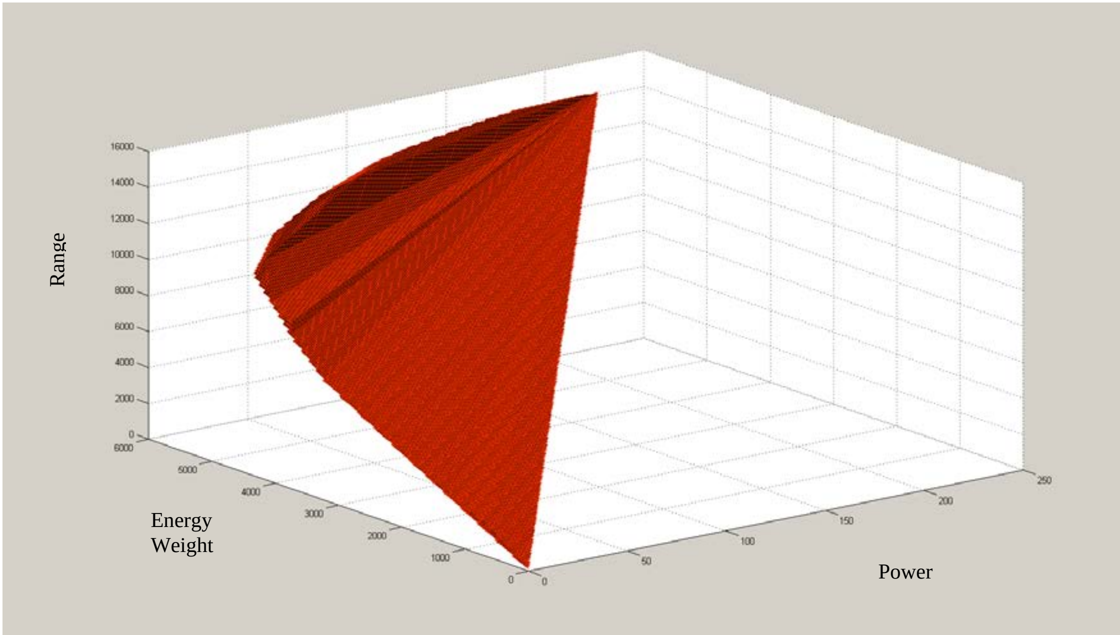

Figure 39. Matlab 3D Pareto Front Surface for Three Objectives Optimization Problem with Speed as a Variable.

4. Fourth Optimization Study

Now, I will show a case in which the designer wishes to have specific values for one or all objectives. These will be the goals to be achieved, as the contradictory nature of the objectives would probably not satisfy all objectives. The classic way of dealing with goals is the goal programming method, which attempts to find solutions that satisfy the goals to the greatest extent. I have already mentioned that an inherent drawback of this and other a priori methods is the obligation of the designer to specify a set of weight factors which correlate with the subjective view of the objectives' importance. In every run the user gets a solution that corresponds to the weight factors given.

By using multi-objective GAs, the user can find multiple PO solutions, each corresponding to a different set of the weight factors. Moreover, that method is not likely to have any difficulty in finding solutions for problems having non-convex feasible decision space [67]. The goals in that case are converted to objective functions consisting of the minima of the deviations. Table 9 gives an overall view of the procedure. I also

need to mention that the bracket operator $\langle\ \rangle$ returns the value of the operand if the operand is positive; otherwise, it returns zero.

Type	Goal	Objective Function
$\leq$	$f_j\left(\bar{x}\right) \leq t_j$	Minimize $\left\langle f_j\left(\bar{x}\right) - t_j \right\rangle$
$\geq$	$f_j\left(\bar{x}\right) \geq t_j$	Minimize $\left\langle t_j - f_j\left(\bar{x}\right) \right\rangle$
$=$	$f_j\left(\bar{x}\right) = t_j$	Minimize $\left\| f_j\left(\bar{x}\right) - t_j \right\|$
Range	$f_j\left(\bar{x}\right) \in \left[t_j^l, t_j^u\right]$	Minimize $\max\left(\left\langle t_j^l - f_j\left(\bar{x}\right)\right\rangle, \left\langle f_j\left(\bar{x}\right) - t_j^u \right\rangle\right)$

Table 9. Formulation of Objective Functions from Goals. From [67].

Once all PO solutions are found, the decision maker can use other approaches to choose one particular solution. It is easier to choose among given alternatives rather than trying to find the best solution by running optimizations with various combinations. After having all the PO points, one can find the relative importance of each objective similarly to the use of weight factors as follows:

$$w_j = \frac{\left|t_j\right| / \left|f_j\left(x\right) - t_j\right|}{\sum_{i=1}^{M} \left|t_i\right| / \left|f_i\left(x\right) - t_i\right|} \quad [67]$$

Furthermore, the drawbacks of the weighted goal programming method do not exist, and there is no difficulty in scaling the criterion function values [67]. Let us assume that the designer needs to find the best solution for the design parameters of the AUV by setting the power needed for overcoming the vehicle resistance at a speed of 2.1 m/sec to be 300 hp, the energy section weight to be 1500 kg and a range of 5000 km. I minimize the absolute value of the difference of the function value with the specific value (see Appendix A, function auv_multiobjective.m) and the results are shown in Table 10.

From the last columns of the table that contain the weightings, the designer can pick one solution according to the importance of each objective.

EHP	Weight	Range		D	L	nf	na		WF EHP	WF Weight	WF Range
312.805	1500.013	5250.035		0.967	6.683	5.505	2.569		0.000	1.000	0.000
316.033	1500.067	5226.343		0.947	6.821	5.105	2.870		0.001	0.998	0.001
300.647	1596.131	5000.010		0.951	6.617	5.292	2.278		0.001	0.000	0.999
314.756	1501.259	5239.962		0.957	6.799	5.370	2.570		0.016	0.967	0.017
303.618	1501.819	5325.969		1.046	6.505	5.697	1.538		0.090	0.894	0.017
312.174	1516.408	5197.312		0.952	6.606	5.230	3.268		0.174	0.647	0.179
304.231	1505.010	5297.074		1.034	6.501	5.204	1.689		0.183	0.773	0.043
310.495	1521.706	5191.146		0.959	6.618	5.369	2.820		0.231	0.558	0.211
308.810	1537.865	5146.769		0.955	6.671	5.413	2.579		0.316	0.368	0.316
302.867	1584.596	5024.943		0.951	6.616	4.386	2.570		0.324	0.055	0.621
306.256	1558.315	5093.368		0.953	6.667	5.184	2.492		0.377	0.202	0.421
301.151	1590.951	5014.784		0.954	6.633	5.165	2.225		0.424	0.027	0.550
304.947	1540.157	5167.222		0.983	6.602	5.383	2.058		0.474	0.292	0.234
303.683	1567.779	5078.676		0.962	6.639	5.130	2.239		0.487	0.132	0.380
303.433	1564.857	5090.871		0.966	6.597	5.274	2.259		0.528	0.140	0.332
301.450	1519.210	5267.836		1.046	6.505	4.697	1.538		0.681	0.257	0.061
300.822	1584.825	5038.983		0.964	6.617	5.240	2.092		0.714	0.035	0.251
301.908	1543.555	5177.799		1.004	6.507	5.203	1.876		0.715	0.157	0.128
300.138	1582.339	5054.845		0.974	6.656	5.575	1.797		0.952	0.008	0.040
300.000	1600.220	5009.904		0.952	6.606	5.230	2.268		1.000	0.000	0.000

Table 10. Results of Three Objectives Optimization with Goals and Weightings.

5. Fifth Optimization Study

One notably interesting case is when one has all the parameters given and he needs to change only the aft and forward form factors n_a and n_f to find the optimum solution. In Table 11 one can see the results of finding the PO of the objectives with D, L and V given, and n_a, n_f as variables.

EHP	Weight	Range		nf	na		
54.74	90.15	498.18		1.00	1.00		D=0.5
63.45	108.60	588.69		1.04	1.86		L=3.1
57.76	96.05	527.25		1.07	1.15		nf
57.99	96.49	529.38		1.08	1.15		na
70.08	123.79	661.36		1.10	3.12		V=2.1
63.12	107.37	582.41		1.12	1.62		
64.19	109.52	592.67		1.18	1.66		
60.52	101.45	553.45		1.34	1.07		
65.89	112.87	608.55		1.35	1.60		
61.83	104.15	566.54		1.38	1.14		
61.38	103.31	562.56		1.46	1.03		
66.84	114.86	618.00		1.50	1.52		
76.70	137.66	725.04		1.69	3.16		
68.58	118.77	636.61		1.71	1.52		
79.51	144.39	755.96		1.90	3.67		
71.40	125.20	666.97		1.90	1.72		
72.94	128.75	683.61		1.97	1.90		
83.66	154.75	803.10		2.61	4.15		
77.82	141.10	741.39		3.21	2.03		
82.74	153.02	795.69		3.60	3.00		
73.99	133.04	704.80		3.77	1.39		
87.79	165.92	853.64		4.43	4.82		
71.66	128.73	685.38		4.52	1.10		
75.76	137.47	725.50		4.57	1.50		
80.05	147.20	769.76		4.62	2.13		
74.70	135.39	716.14		4.97	1.35		
87.15	164.63	848.13		5.43	4.11		
89.40	170.39	873.73		5.92	5.34		
90.20	172.45	882.81		5.95	6.00		

Table 11. Results of Three Objectives Optimization Using n_f and n_a as Variables.

I used the Matlab commands *cylinder* and *surf* (see Appendix A, function volume_hull_2.m) to obtain the plots of the hull geometry for different cases, as can be seen in Figures 40, 41, 42 and 43.

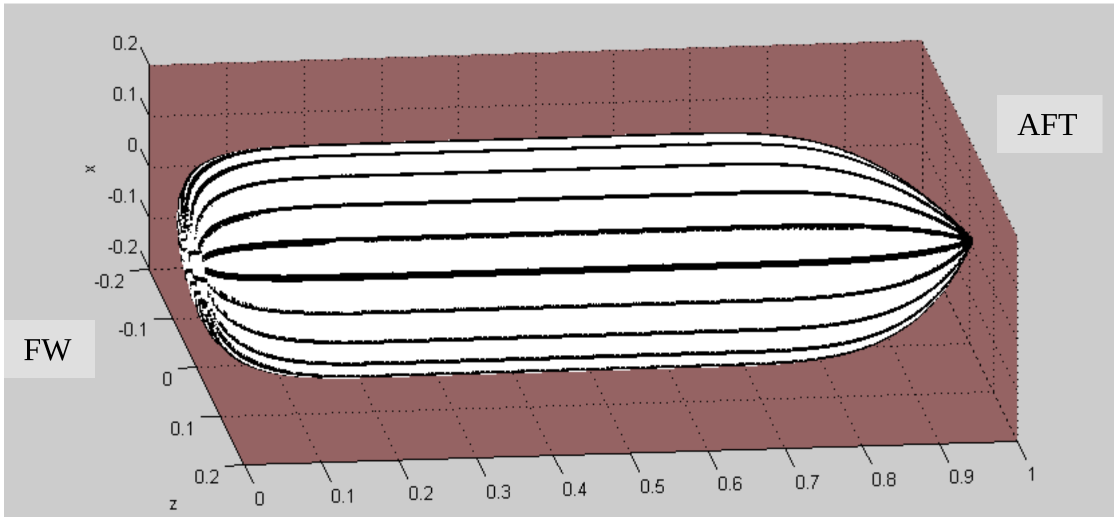

Figure 40. Hull Geometry of an AUV with Form Factors n_f =3.60 and n_a =3.00.

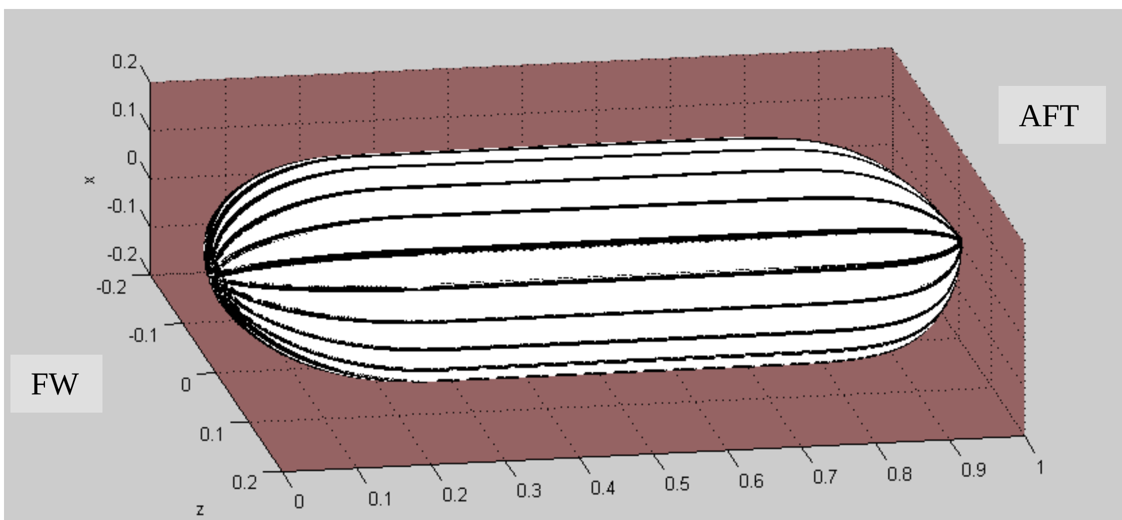

Figure 41. Hull Geometry of an AUV with Form Factors n_f =2.61 and n_a =4.15.

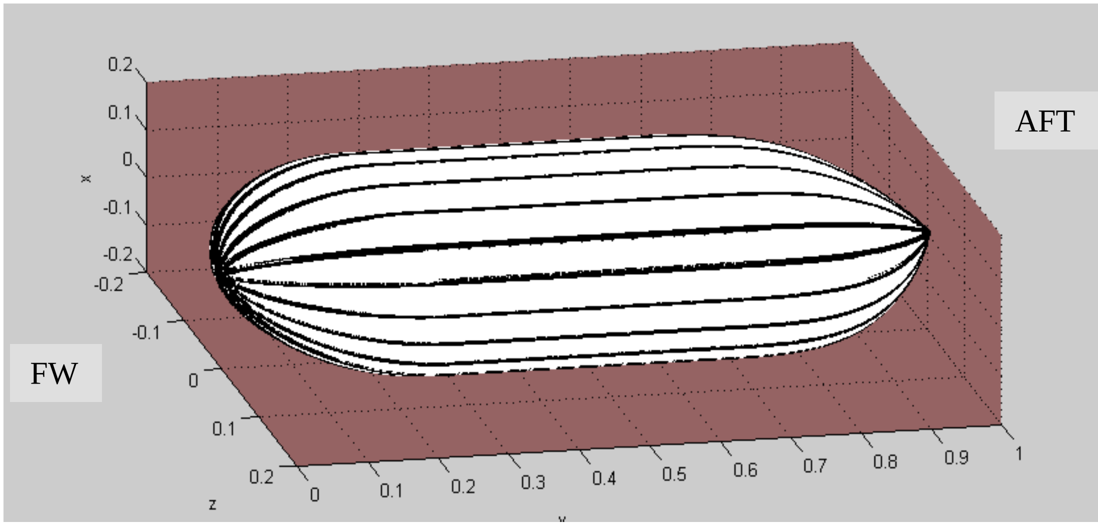

Figure 42. Hull Geometry of an AUV with Form Factors n_f =1.90 and n_a =3.67.

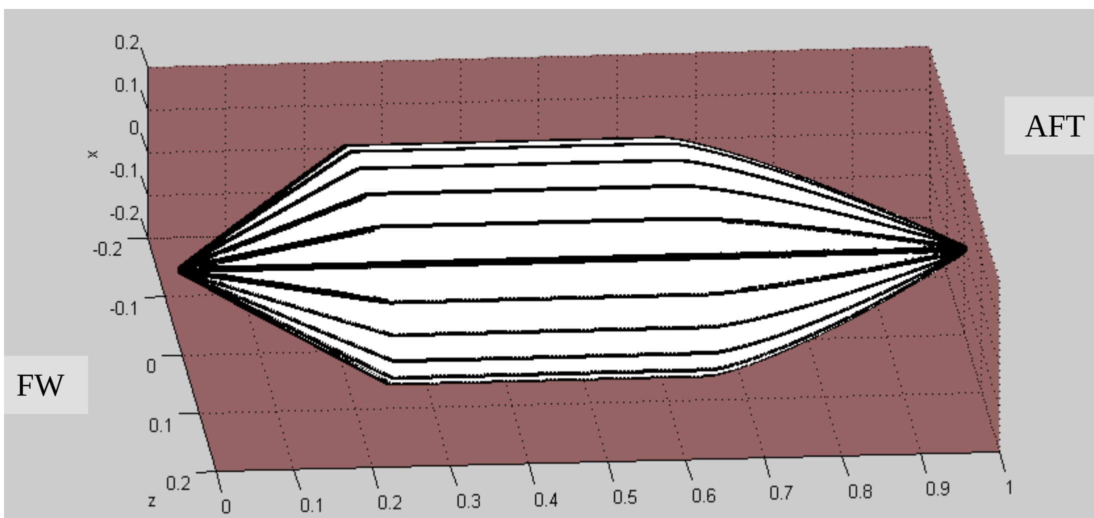

Figure 43. Hull Geometry of an AUV with Form Factors n_f =1.04 and n_a =1.86.

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V. CONCLUSIONS AND RECOMMENDATIONS

This study presented a preliminary design process to identify the design space of some given AUV objectives and to conduct a multi-objective optimization. It used multi-objective optimization to integrate multiple disciplines so that total-system decisions can be made.

An AUV model was created using the objectives of the power needed to propel the vehicle, the weight of the energy section and the total range. The validity of the model was checked using inputs from various sources. Implementation of both the model and the optimization was carried out using Matlab. The global optimization toolbox and the multi-objective genetic algorithm solver were used as regards the optimization, whereas a special case of two objectives was implemented in Excel using Visual Basic and Excel Solver.

The designer's ability to use goals in the multi-objective optimization, as well as approaches that let a designer choose one particular solution once all PO solutions are found, were also explored.

There are many aspects of the AUV design that could be considered for improving the current model. I only used some design criteria to demonstrate how a preliminary design works using multi-objective optimization. The following can be used as recommendations for further research, even though much more can be added.

An objective of minimizing the total construction cost can be added. Materials, man-hours and development costs could also be included.

A structural analysis using finite elements methods and some object arrangement algorithm would be important model advancements. A designer would need to optimize the placement of the devices that affect the center of gravity as well.

Incorporating risk in a quantitative way into the model would increase its accuracy. Technology risks based on selection of components or other risks related to performance and schedule issues could be considered.

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APPENDIX A. MATLAB FILES

```
function ehp=power_auv(x)

%=====================================================================
% LCDR Sotirios Margonis - Thesis work
%=====================================================================
% This function calculates the power needed for an AUV.
% I use a cylindrical hull following MIT model (Jackson 1992).
% It assumes a body of revolution with a length/diameter (L/D)
% ratio of 6 and a maximum diameter at 0.4L. The entrance has a length,
% Lf=2.4D. The run or after end has a length, La=3.6D.
%=====================================================================

Diameter=x(1);   Loa=x(2);    nf=x(3);   na=x(4);

%x(5)=2.1;            When speed is given (m/sec - 4 Knts)
Velocity=x(5);        % When speed is a variable

format long;
ca=0.0004;            %typical value (or 0.0002)
rho=1025;             %sea water density kg/m^3
mhu=0.00108;          %kg/(m*sec)

Re=Loa*Velocity*rho/mhu;                             %Reynold's number
S=surface_hull_2([Diameter Loa nf na]);              %Wetted surface
cf=0.075/(log10(Re)-2)^2;                            %Bare-hull skin
friction coefficient
formfac=1+0.5*Diameter/Loa+3*(Diameter/Loa)^3;       %The coefficient of
viscous resistance(multiplied by cf)
Rapp=1/1000*Loa*Diameter;                            %Account for
appendages - Vlahopoulos Hart
Rt=1/2*rho*Velocity^2*(S*(cf*formfac+ca)+Rapp);      %Resistance
ehp=Rt*Velocity;                                     %EHP Effective
horse power
```

```
function W_power=weight_energy(x)

%======================================================================
% LCDR Sotirios Margonis - Thesis work
%======================================================================
% This function calculates the weight of the energy section of an AUV.
% It assumes a hull thickness of 6mm.
% It assumes a material density of 2700 kg/m3 (Aluminum).
%======================================================================

Diameter=x(1);   Loa=x(2);    nf=x(3);   na=x(4);

t=0.006;              %hull thickness (m)
rho_sea=1025;         %sea water density (kg/m^3)

%rho_material=8000;   % Steel:8000(kg/m^3)
rho_material=2700;    % Aluminum:2700
%rho_material=1750;   % GRP:1750

format long;
V_outer=volume_hull_2([Diameter Loa nf na]);
inner_diameter=Diameter-2*t;
loa_inner=Loa-2*t;
V_inner=volume_hull_2([inner_diameter loa_inner nf na]);

W_tot=V_outer*rho_sea;      %The total weight of the AUV
W_hull=(V_outer-V_inner)*rho_material; %The weight of the hull
if W_hull>0.2*W_tot
    W_hull=0.2*W_tot;       %It sets a limit to the weight of the hull
end
W_prop=0.1*W_tot;           %The weight of the propulsion system
W_append=0.05*W_tot;        %The weight of the appendages
W_payload=0.4*W_tot;        %The weight of the payload
W_power=W_tot-W_hull-W_prop-W_append-W_payload;
%The weight of the energy section equals to the total weight minus the
weights of the hull, the propulsion system, the appendages and the
payload
```

```
function range=range_auv(x)

%=======================================================================
% LCDR Sotirios Margonis - Thesis work
%=======================================================================
% This function calculates the range of an AUV.
% A hybrid energy system is assumed with an energy density of 0.5
kWh/kg.
% It assumes a hotel load of 600 hp.
% It uses an overall propulsion coefficient PC=0.65.
%=======================================================================

Diameter=x(1);   Loa=x(2);    nf=x(3);   na=x(4);

%x(5)=2.1;             When speed is given (m/sec - 4 Knts)
Velocity=x(5);        % When speed is a variable

format long;

energy_density=0.5;   %kWh/kg - Hybrid Energy System

%ehp=resistance_auv_power_source_5([Diameter Loa nf na]);
ehp=power_auv([Diameter Loa nf na Velocity]);

nH=1.0;                        %hull efficiency (1-t)/(1-w)
nR=0.98;                       %relative rotative efficiency (open
water - hull wake)
nO=0.70;                       %open water efficiency (propeller type,
diameter, rpm etc)
nM=0.95;                       %machinery efficiency (rotor, bearings,
shaft)

Etot=1000*weight_energy([Diameter Loa nf na])*energy_density; %Wh
p_hotel=600;                   %Hotel load (Watt)

n_prop=nH*nR*nO*nM;                            %overall propulsive
efficiency
%n_prop=0.65;
duration=Etot*n_prop/(ehp+p_hotel*n_prop);     %in hours (Wh/W)
range=(duration*Velocity*3.6);                 %in km
```

```
function Surface=surface_hull(x)

%==================================================================
% LCDR Sotirios Margonis - Thesis work
%==================================================================
% This function calculates the wetted surface of the hull of an AUV.
% It uses a cylindrical hull following MIT model (Jackson 1992).
% It assumes a body of revolution with a length/diameter (L/D)
% ratio between 6 and 9 and a maximum diameter at 0.4L. The entrance
% has a length Lf=2.4D. The run or after end has a length, La=3.6D.
% It uses the int() Matlab function but the time needed is much higher
% than using surface_hull_2(x)
%==================================================================

Diameter=x(1);   Loa=x(2);    nf=x(3);   na=x(4);
Lf=2.4*Diameter;  La=3.6*Diameter;

Lpmb=Loa-La-Lf;

syms x;
s1=pi*Diameter*int((1-(1-x/Lf)^nf)^(1/nf), x,0,Lf);
s1=vpa(s1,5);

s2=pi*Diameter*(Loa-La-Lf);
s2=vpa(s2,5);

s3=pi*Diameter*int(1-((x-Lf-Lpmb)/La)^na,x,Loa-La,Loa);
s3=vpa(s3,5);

Surface=s1+s2+s3;
```

```matlab
function Surface=surface_hull_2(x)

%======================================================================
% LCDR Sotirios Margonis - Thesis work
%======================================================================
% This function calculates the wetted surface of the hull of an AUV.
% It uses a cylindrical hull following MIT model (Jackson 1992).
% It assumes a body of revolution with a length/diameter (L/D)
% ratio between 6 and 9 and a maximum diameter at 0.4L.
% The entrance has a length Lf=2.4D. The run or after end has a length,
% La=3.6D. It uses a numerical approximation (Discretization with
% n=1000)
%======================================================================

Diameter=x(1);   Loa=x(2);    nf=x(3);   na=x(4);
Lf=2.4*Diameter;  La=3.6*Diameter;

Lpmb=Loa-La-Lf;

n=1001;
a=[1:1:n];
dx=a*Loa/n;
bf=Lf*n/Loa;
bf=floor(bf);
xf=dx(1:bf);
ba=(Loa-La)*n/Loa;
ba=floor(ba);

xa=dx(ba+1:n);

for i=1:bf
    y=Diameter/2*(1-((Lf-xf)/Lf).^nf).^(1/nf);
end

j=1;
for i=bf+1:ba
    y(i)=Diameter/2;
    j=j+1;
end

j=1;
for i=ba+1:n
    y(i)=Diameter/2*(1-((xa(j)-Lf-Lpmb)/La).^na);
    j=j+1;
end

v=2*pi*y;
Surface=trapz(dx,v);
```

```
function Volume=volume_hull(x)

%=======================================================================
% LCDR Sotirios Margonis - Thesis work
%=======================================================================
% This function calculates the volume of the hull of an AUV.
% It uses a cylindrical hull following MIT model (Jackson 1992).
% It assumes a body of revolution with a length/diameter (L/D)
% ratio between 6 and 9 and a maximum diameter at 0.4L. The entrance
% has a length Lf=2.4D. The run or after end has a length, La=3.6D.
% It uses the int() Matlab function but the time needed is much higher
% than using volume_hull_2(x)
%=======================================================================

Diameter=x(1);   Loa=x(2);    nf=x(3);   na=x(4);
Lf=2.4*Diameter;  La=3.6*Diameter;
Lpmb=Loa-La-Lf;

format long;

syms x;
v1=Diameter^2/4*pi*int(((1-(1-x/Lf)^nf)^(1/nf))^2, x,0,Lf); %yf=D/2*{1-
(Lf-xf)....
v1=vpa(v1,5);

v2=vpa(Diameter^2/4*pi);
v2=int(v2,Lf,Loa-La);

v3=Diameter^2/4*pi*int((1-((x-Lf-Lpmb)/La)^na)^2,x,Loa-La,Loa);
v3=vpa(v3,5);

Volume=(v1+v2+v3);
```

```
function Volume=volume_hull_2(x)

%=======================================================================
% LCDR Sotirios Margonis - Thesis work
%=======================================================================
% This function calculates the volume of the hull of an AUV.
% It uses a cylindrical hull following MIT model (Jackson 1992).
% It assumes a body of revolution with a length/diameter (L/D)
% ratio between 6 and 9 and a maximum diameter at 0.4L.
% The entrance has a length Lf=2.4D. The run or after end has a length,
% La=3.6D. It uses a numerical approximation (Discretization with
% n=1000)
%=======================================================================

Diameter=x(1);   Loa=x(2);    nf=x(3);   na=x(4);
Lf=2.4*Diameter;  La=3.6*Diameter;
Lpmb=Loa-La-Lf;

format long;

n=1001;
a=[1:1:n];
dx=a*Loa/n;
bf=Lf*n/Loa;
bf=floor(bf);
xf=dx(1:bf);
ba=(Loa-La)*n/Loa;
ba=floor(ba);
xa=dx(ba+1:n);

for i=1:bf
    y=Diameter/2*(1-((Lf-xf)/Lf).^nf).^(1/nf);
end

j=1;
for i=bf+1:ba
    y(i)=Diameter/2;
    j=j+1;
end

j=1;
for i=ba+1:n
    y(i)=Diameter/2*(1-((xa(j)-Lf-Lpmb)/La).^na);
    j=j+1;
end

v=pi*y.^2;
Volume=trapz(dx,v);
% If we want to plot an AUV hull
%[Z,X,Y] = cylinder(y);
%surf(X,Y,Z)
%xlabel('z'); ylabel('y'); zlabel('x')
%view(60,20)
```

```
function y = auv_multiobjective(x)

%=======================================================================
% LCDR Sotirios Margonis - Thesis work
%=======================================================================
%The function AUV_MULTIOBJECTIVE computes two or three
%   objectives and returns a vector y of size 2-by-1 or 3-by-1.
%=======================================================================

y=[];
% Initialize for two/three objectives
y(1)=power_auv([x(1) x(2) x(3) x(4) x(5)]);
y(2)=-weight_energy([x(1) x(2) x(3) x(4) x(5)]);
y(3)=-range_auv([x(1) x(2) x(3) x(4) x(5)]);

%When we need to use goals
%y(1)=abs(power_auv([x(1) x(2) x(3) x(4)])-300);
%y(2)=abs(weight_energy([x(1) x(2) x(3) x(4)])-1500);
%y(3)=abs(range_auv([x(1) x(2) x(3) x(4)])-5500);

%If we want to find one point in the Pareto front
%Known preferences/weights
%y1=power_auv([x(1) x(2) x(3) x(4)]);
%y2=-weight_energy([x(1) x(2) x(3) x(4)]);
%y3=-range_auv([x(1) x(2) x(3) x(4)]);
%y=0.84*y1+0.07*y2+0.09*y3;
```

APPENDIX B. EXCEL MODEL

Autonomous Underwater Vehicle Design

Please choose the external diameter, overall length, form factor coefficients and speed

D(m)	Loa(m)	nf	na	V
1.00	7.00	3.00	3.00	0.50
1.000	7.000	3.000	3.000	

n
2000

Ca	mhu	rho	Viscosity
0.0004	0.00108	1025	1.0537E-06

Thickness	rho_material
0.006	2700

These are the calculated outputs

Lf	La	Lpmb
2.4	3.6	1
2.400	3.600	1.000

Vf	Vpmb	Va	Vtot
1.51953339	0.785398163	1.81905	4.123981243

Sf	Spmb	Sa	Stot
6.65998479	3.141592654	8.488002	18.2895796

formfac	Re	Rapp	Cf	Rt	EHP
1.080174927	3321759.259	0.007	0.00366878	11.12074058	5.5603703

Inner_diam	Inner_loa
0.988	6.988
0.988	6.988

Lf	La	Lpmb
2.3712	3.5568	1.06
2.371	3.557	1.060

V_Inner

Vf	Vpmb	Va	Vtot
1.46530442	0.812661407	1.754427	4.032392936

V_outer	V_inner	W_tot	W_hull	W_prop	W_append	W_payload	W_power
4.123981243	4.032392936	4227.081	247.288429	422.7080774	211.35404	1690.83231	1654.89792

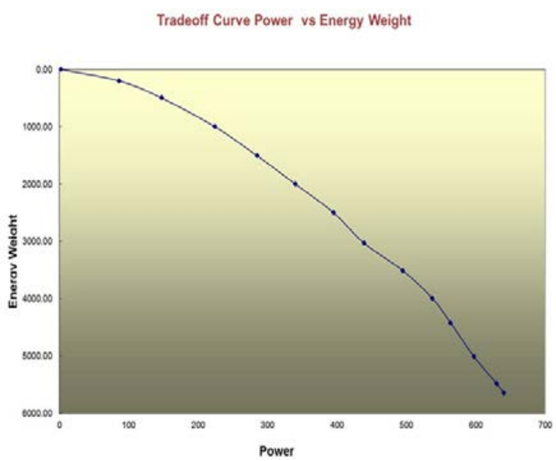
W_power>	EHP	W_power	D	L	nf	na	V
0.44	2.533984	-0.44	0.10	0.60	1.00	1.00	2.06
200	86.09805	-200.14	0.62	3.7	1.05	1.92	2.06
500	147.1993	-497.34	0.82	4.95	1.05	1.92	2.06
1000	223.9813	-998.28	1.03	6.19	1.05	1.92	2.06
1500	285.0312	-1505.47	1.18	7.05	1.05	1.92	2.06
2000	340.045	-1998.86	1.280	7.710	1.050	1.920	2.06
2500	395	-2496.95	1.38	8.28	1.05	1.92	2.06
3000	439.1169	-3029.45	1.45	8.97	1.05	1.92	2.06
3500	494.9336	-3507.88	1.27	9	3.38	2.59	2.06
4000	537.4575	-3991.46	1.27	9	5	5.5	2.06
4500	563.6612	-4418.53	1.33	9	5	5.5	2.06
5000	597.2013	-5004.52	1.41	9	5.39	5.65	2.06
5500	629.9659	-5475.38	1.49	8.95	5.78	5.7	2.06
5639	640.41	-5639.12	1.5	9	6	6	2.06

Parameter Definitions:

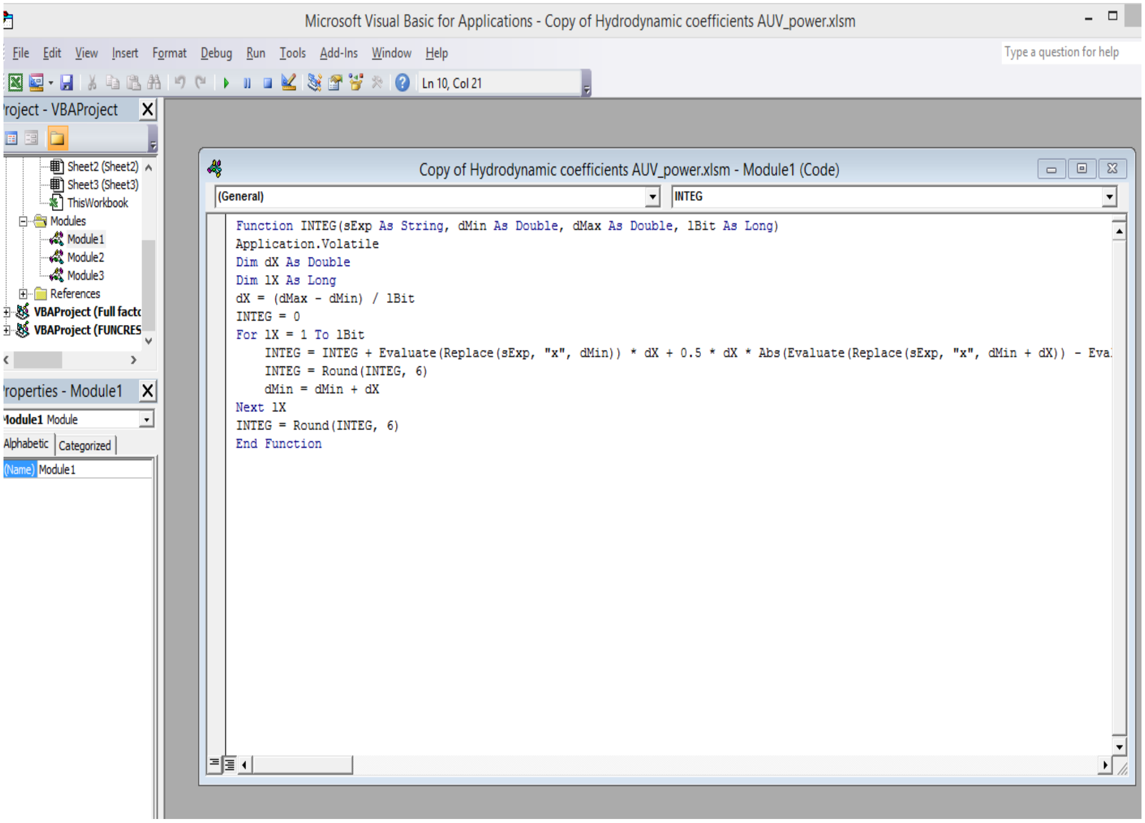
D: Maximimum hull diameter (m)
Loa: Overall length (m)
nf: Forward form factor
na: Aft form factor
Lf: Forward length (m)
La: Aft length (m)
Lpmb: Length of the parallel midbody (m)
V: Speed of vehicle (m/sec)
n: Discretizations of hull

Vtot: Overall volume of the hull
Re: Reynolds number
Cf: Bare jull skin friction coefficient
Stot: Overall wetted surface
formfac: Form factor coefficient

ca: Correlation Allowance coefficient typical value (or 0.0002)
rho: Sea water density Kg/m^3
mhu: (mhu/rho: Sea water kinematic viscosity) Kg/(m*sec)



Microsoft Visual Basic Function that calculates the integral numerically:



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